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Differentiating oil palm plantations from natural forest to improve land cover mapping in Ghana

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ABSTRACT

Tree crops like oil palm present a unique challenge in land cover mapping, as they are often misclassified as natural forest. The area cultivated with oil palm in Ghana has rapidly expanded since 2000, and production is expected to continue to increase. Sentinel-1 and Sentinel-2 satellite data was used as inputs to a random forest classifier in Google Earth Engine to map mature, closed-canopy oil palm extent in 2019 of a Ghana study area that includes both industrial plantations and smallholders. The combination of Sentinel-1 and Sentinel-2 bands and derived indices outperformed either satellite alone for mapping industrial oil palm (90.3% overall accuracy). A separate accuracy assessment for this combined input approach demonstrated high accuracy mapping smallholders as well (80.4% overall accuracy), a key challenge in the West African context. To validate these findings, results were compared with available production information and a global oil palm remote sensing product. The resulting map can inform sustainable oil palm efforts in Ghana, which is understudied in current oil palm remote sensing literature, and the methodology provides an example for future studies of oil palm sourcing areas using only publicly available data.

1. Introduction

Tropical forests are vital to the global environment and climate system. They sequester carbon, host large amounts of biodiversity, and provide many other valuable ecosystem services (Ninan and Kontoleon, 2016; Acharya et al., 2019, FAO, 2020a). The Guinean Forests of West Africa were identified as a global biodiversity hotspot over 20 years ago (Myers et al., 2000), yet only about 10% of its estimated original primary vegetation remains (CILSS, 2016). Expansion of low-input, low-yield agriculture has been the main driver of this deforestation, and about 80% of the original forested lands in West Africa now exist as an agriculture-forest mosaic (Norris et al., 2010). In Ghana, the remaining portions of undisturbed forest are primarily within a patchwork of forest and nature reserves (CILSS, 2016). Further destruction of forest ecosystems could have major consequences for Ghana's predominantly agricultural economy and the global climate (Forestry Commission of Ghana, 2021).

Uncertainty on forest extent and even the definition of a forest limits the effectiveness of forest related policy (Sasaki and Putz,

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2009; Sexton et al., 2016). While the forest definitions of the UN Food and Agriculture Organization (FAO) and the Forestry Commission of Ghana differ on minimum area and canopy covers thresholds for forest, they both specifically exclude oil palm plantations (FAO, 2020a; Forestry Commission of Ghana, 2021). However, many commonly used land cover products classify oil palm plantations as a forest or general tree cover class (Fig. A1). Natural forests are much more effective at carbon sequestration (Kho and Jepsen, 2015; Anokye et al., 2021) and protecting tropical biodiversity (Fitzherbert et al., 2008; Gibson et al., 2011; Savilaasko et al., 2014).

Little attention is given to studying commodity-driven deforestation in sub-Saharan Africa, however, the African oil palm industry is expected to continue expanding in the future (Hansen et al., 2015; Rhebergen et al., 2016; Ordway et al., 2019). Cultivated area of oil palm in Ghana has more than doubled from 160,000 ha in 2000 to 355,519 ha in 2019 (Fig. A2). While global deforestation rates decreased in 2010–2020 compared to the previous decade, African deforestation rates increased and were the highest of any region in the world (FAO, 2020b), prompting fears of a deforestation shift to Africa.

The methods developed for oil palm remote sensing in southeast Asia or global contexts must be tested in West African study areas. While in Malaysia and Indonesia smallholders make up 40% of the oil palm concessions by area, in Ghana the smallholder area is 93% (Meijaard et al., 2018). Smallholders are often more difficult to detect (Cheng et al., 2018; Descals et al., 2021) due to the presence of mixed pixels that impact signals, resulting from a variety of factors like smaller field sizes, irregular field boundaries, intercropping of fields, and lack of full canopy closure resulting from farming practices (Descals et al., 2019, 2021). Ghanaian oil palm smallholder plantations typically range from 0.5 to 5 ha, while industrial plantations can cover thousands of hectares (Meijaard et al., 2018). Therefore, methods that do not accurately map smallholders will perform poorly for the vast majority of oil palm areas in Ghana.

This research applies the knowledge gained in mapping oil palm in southeast Asia to the understudied and data-scarce Ghanaian landscape. The limited spatial information available comes from the Roundtable on Sustainable Palm Oil (RSPO), which only accounts for certified plantations. As certification is more frequently achieved by industrial plantations, this accounts for less than 9% of the oil palm cultivated area reported by the FAO in 2019. This paper aims to (i) evaluate the accuracy of a random forest classification for mapping mature, closed-canopy oil palm in Ghana using Sentinel-1 data only, Sentinel-2 data only, and a combination of both inputs. Next it (ii) compares industrial oil palm plantation accuracy to smallholder oil palm accuracy. Finally, it (iii) validates the oil palm classification result using available information in the data-scarce region.

2. Data and methods

2.1. Study area

The study area is located in the Eastern Region of Ghana, its leading palm oil producing region (MASDAR, 2011; United States Department of Agriculture and Foreign Agricultural Service, 2017). A 50-km buffer region was created around Kwae plantation's mill to define the study area (Fig. 1). Since palm oil must reach the mill in 24 hours or less to preserve its quality, and a 50-km road network represents the maximum distance that can likely be traveled in this timeframe in Ghana, this buffer approximates the mill's likely sourcing area (Harris et al., 2019). The area includes two large industrial oil palm plantations certified by the RSPO, as well as the smallholder network surrounding them. Agriculture employs most people in the area, as well as the operation of small-scale oil palm processing mills (Osei-Amponsah et al., 2012). The forest reserves in the area contain undisturbed primary forest land cover. The study period is 2019, allowing for results to be compared with the results of Descals et al. (2021), a global remote sensing study with the only other publicly available maps of oil palm in Ghana. Since oil palm is a perennial tree crop without much phenological change

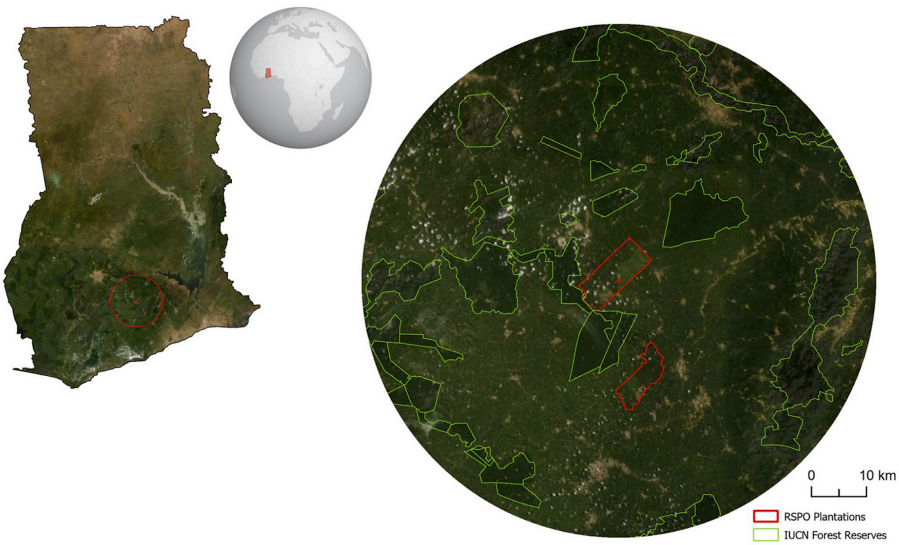

Fig. 1. 50-kilometer buffer around Kwae plantation mill serving as study area. Base map data sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FAS, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

throughout the year in its tropical environment once it reaches its mature, closed-canopy stage, data can be collected throughout the year without much variation (Forero et al., 2011). However, only dry season (December 2018–February 2019) data was used to minimize impacts of cloud cover and rainfall on results.

2.2. Data

2.2.1. Sentinel-1

Synthetic aperture radar (SAR) data from the European Space Agency's (ESA) Sentinel-1 constellation of two C-band SAR satellites was used, accessed through the Alaska Satellite Facility. As an active microwave radar it can collect data regardless of solar illumination and due to wavelength it is not influenced by atmospheric conditions like cloud cover. This is extremely beneficial when working in frequently cloudy environments like tropical West Africa (Simard, 2019). Both the vertical transmit vertical receive (VV) and vertical transmit horizontal receive (VH) polarizations were used. Prior to download, radiometric terrain correction (RTC) and an Enhanced Lee Filter were applied to each scene. The digital elevation model (DEM) used for the RTC process was the Copernicus 30-m DEM, resulting in scenes with 30-m resolution.

Despite SAR's ability to penetrate clouds, C-band SAR data can be influenced by heavy rain events that impact soil and vegetation moisture content (Kellndorfer, 2019). To minimize the impact of rainfall on surface backscatter response, scenes used were selected from December 2018 through February 2019, the driest months of the year in southern Ghana. Of the available scenes from this period, further analysis was done using Global Precipitation Measurement (GPM) mission data to ensure no heavy rainfall events occurred in the study area on the date of Sentinel-1 data acquisition or the two days before. Only scenes within the dry season that had no recent heavy rainfall were selected for use in this study. As a result, the specific scene dates used were December 24 (2018), January 10 (2019), January 22 (2019), and February 15 (2019).

2.2.2. Sentinel-2

Multispectral remote sensing data was used from ESA's Sentinel-2 constellation. These passive sensors operate at visible, near infrared (NIR), and shortwave infrared (SWIR) wavelengths, which are influenced by cloud cover. Sentinel-2 bands 2 through 12 were used in this research. This data is hosted on the Google Earth Engine (GEE) platform as already corrected surface reflectance values (Gorelick et al., 2017). Sentinel-2 was chosen over Landsat 8 due to its higher spatial resolution that can be helpful for mapping smallholder oil palm plantations (Nomura and Mitchard, 2018), as well as its lower revisit time that provides a higher chance of cloud free data. Scenes over the study area from January 1, 2019 to March 1, 2019 were used.

2.2.3. Ancillary datasets

As no field data was collected on the ground for this research, high-resolution imagery was required to record reference data for training and validation of the random forest classification. The satellite base map provided on GEE was used for this purpose. While the dates of individual images on the GEE base map are not provided, they are generally less than two years old (Descals et al., 2021). This imagery has been successfully employed for mapping oil palm (Descals et al., 2021) due to their replanting cycles of roughly 25–30 years and their perennial nature.

Several shapefiles were used to assist in reference data collection. Polygon borders of certified oil palm plantations were gathered from the RSPO. Only the borders of the large industrial plantations within the study area, Kwae and Okumaning, were used, as they were validated through analysis of high-resolution imagery. Spatial information on forest reserves was used as well, downloaded from the World Database on Protected Areas (WDPA). These boundaries were used to define natural forest areas in this study, as forest reserves contain the only areas of undisturbed primary forest remaining in Ghana (CILSS, 2016).

2.3. Methods

2.3.1. Preprocessing

The overall methodology is shown in Fig. 2. For Sentinel-1 data, median compositing of scenes was conducted after the selection process using GPM data to disqualify scenes with recent rainy days (Section 2.2.1). This was done separately for VV and VH bands of

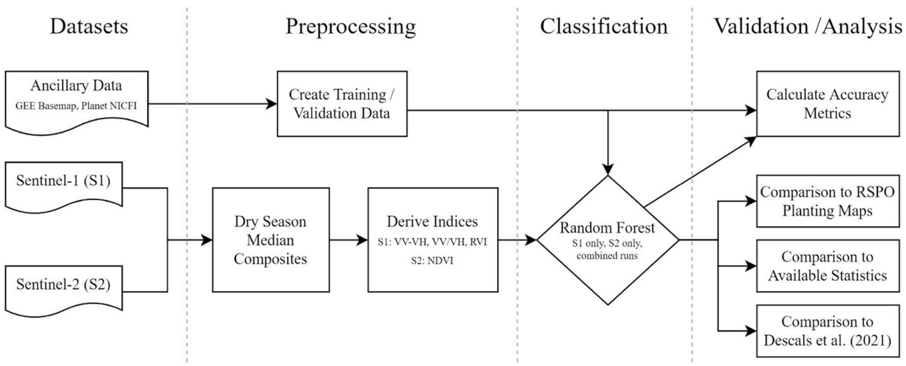

Fig. 2. Methodology overview.

Sentinel-1, resulting in 2019 dry season mosaics for the VV and VH polarizations. For Sentinel-2 data, any scenes with more than 20% cloudy pixels were removed, resulting in 23 useable scenes. Remaining clouds were masked using the Sentinel-2 Quality Assessment (QA) band. A median composite of these scenes was created to further reduce cloud cover. This resulted in a 2019 dry season mosaic for each of the 10 multispectral bands used.

Derived indices were calculated using the median composites to provide additional information to the classifier (Table 1). For Sentinel-1, the derived indices were the ratio of VV to VH (VV/VH), the difference of VV and VH (VV-VH), and the radar vegetation index (RVI). RVI measures volume scattering well, giving useful information on the complex structure of vegetation (Szigarski et al., 2018), and has been adapted for use with Sentinel-1 data (Mandal et al., 2020). For Sentinel-2, the normalized difference vegetation index (NDVI) was calculated, commonly used for approximating vegetation greenness (Huang et al., 2021).

2.3.2. Reference data collection

The creation of training data is extremely important for the performance of random forest classification (Millard and Richardson, 2015; Nomura and Mitchard, 2018). High-resolution (<1 m) imagery from the GEE basemap was used for visual interpretation, rather than collection of field data. At this resolution, oil palm is distinguishable from natural forest and other land covers in the study area due to its unique canopy and planting patterns. A pseudo-stratified random sample was employed to generate points for labeling. Only points within Kwae and Okumaning plantations were included in the training data for oil palm. Points were generated within the WDPA forest reserves to ensure a wealth of natural forest points. Additional random points were labeled throughout the study area to include other land cover types (bare surface, rubber, and other green vegetation).

Additionally, 4.77-m resolution Planet NICFI mosaics (Planet, 2021) for the first half of 2019 (December 2018–May 2019) and the second half of 2019 (June 2019–December 2019) were used to ensure no replanting or land clearing occurred in the time between when basemap imagery was acquired and the study period of 2019. A total of 625 points were labeled oil palm and 625 were labeled natural forest, as well as 271 other land cover class points. Following a random 80%/20% split between training and validation data this resulted in 500 training points for each focus class, following the findings of Li et al. (2015) on the necessary number of training points. A two-tiered label was applied to each point, one label being whether the point is oil palm or not, and the other being what specific land cover it was.

2.3.3. Random forest classification

Random forest classification is widely used in remote sensing, as it has proven to perform well in applications involving a variety of different data inputs (Millard and Richardson, 2015). It has become popular for mapping oil palm, mainly in southeast Asia (Lee et al., 2016; Descals et al., 2019; Sarzynski et al., 2020; Xu et al., 2020). The random forest function built into GEE was used in this study, with 100 decision trees and otherwise default parameters, following Sarzynski et al. (2020). The classification was run with three different combinations of input data: Sentinel-1 bands and derived indices only, Sentinel-2 bands and derived indices only, and bands and derived indices of both satellite data sources combined. The classification results in a binary map of oil palm pixels and non-oil palm pixels.

2.3.4. Accuracy assessment and validation

Error matrices are a common way to assess accuracy in remote sensing studies, offering a simple presentation of correct classifications and errors (Olofsson et al., 2014). The 20% of labeled reference points withheld from training the algorithm were used for validation. Overall accuracy, oil palm class user's accuracy, oil palm class producer's accuracy, and kappa statistic were calculated for each classification. It is important to note that the reference points were drawn only from industrial oil palm plantations certified by RSPO, and as a result all validation pixels are located within these bounds. The accuracy metrics are therefore for industrial oil palm, necessitating a separate smallholder oil palm accuracy assessment to get a true understanding of performance in this smallholder-driven region.

A high resolution (0.48m GSD) Maxar GeoEye-1 image from January 3, 2020 was used for labeling of a separate set of validation data. This image covered a region of the smallholder mosaic surrounding the Kwae plantation, and points were labeled oil palm or non-oil palm (Fig. 3). For each class, 125 points were labeled, matching the amount of validation data per class used in the industrial accuracy assessment. To focus on the performance of the classification on smallholders, random points for labeling were generated outside RSPO plantation boundaries, WDPA forest reserve boundaries and urban areas. As the combined classification outperformed the individual data source classifications for the industrial accuracy assessment, it was the only result assessed for smallholder accuracy.

Further validation of results was conducted using information (RSPO, 2014) reported by the Ghana Oil Palm Development Company, which runs the RSPO certified industrial plantations within the study area. While the available maps were created in 2014, their information on planting dates is helpful for analyzing results of the 2019 classification. The maps were georeferenced to plantation boundary information provided by RSPO data in ArcMap, allowing for classification results to be overlaid and qualitatively assessed. Global forest change data from Hansen et al. (2013) was used to detect tree loss indicating clearing for replanting, providing

Table 1
Derived indices used as classification inputs.

Index	Satellite	Formula
RVI	Sentinel-1	$RVI = 4^* (VH/(VV + VH))$
NDVI	Sentinel-2	$NDVI = (NIR - Red)/(NIR + Red)$

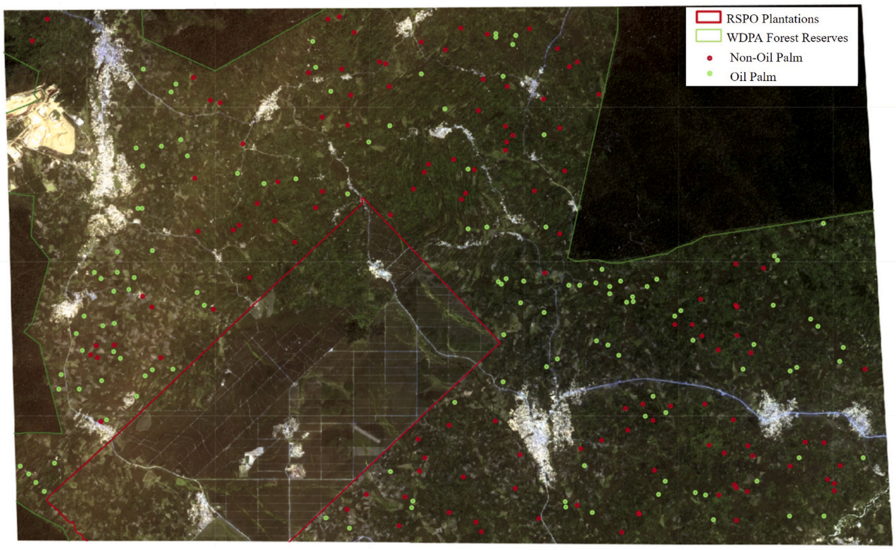

Fig. 3. Independent smallholder accuracy assessment study area with labeled reference points. Basemap data source: Google Imagery, CNES/Airbus, Landsat/Copernicus, Maxar Technologies.

information on the period between 2014 and 2019. Due to a lack of regional or local remote sensing studies, results were also compared with the global classification output of Descals et al. (2021). Their convolutional neural network used a combination of Sentinel-1 and Sentinel-2 data to map oil palm for 2019 at extremely high accuracy globally (98.53% OA), however, the performance of their model regionally varies widely and struggled in West Africa.

2.3.5. Area calculations

Areas of mature, closed-canopy oil palm were calculated using the results of each classification. Oil palm pixels within the Kwae and Okumaning plantation shapefiles were considered industrial and all outside these boundaries in the study area were considered smallholders. Since it was found to be the most accurate, additional postprocessing was applied to the combined classification to reduce noise (Nomura et al., 2019; Xu et al., 2021; Sarzynski et al., 2020) and obtain a more physically realistic area. First, a 3x3 pixel neighborhood mode filter was applied to the results of the combined classification. Next, the raster data was converted into a multi-polygon shapefile and a minimum area threshold was applied to each polygon. Those with areas below 0.5 ha were removed, resulting in a final area calculation for oil palm in the study area with a minimum field size of 0.5 ha, which includes most smallholder oil palm plantations for the region (Meijaard et al., 2018).

Table 2
Error matrices for each classification using industrial oil palm reference data.

Sentinel-1 only (OA = 85.6%) PA = 82.1%, UA = 81.5%, Kappa = 0.699		Reference Data		
		Non oil palm	Oil palm	Total
Classification	Non oil palm	167	22	189
	Oil Palm	23	101	124
	Total	190	123	313
Sentinel-2 only (OA = 84.3%) PA = 78.5%, UA = 77.8%, Kappa = 0.738		Reference Data		
		Non oil palm	Oil palm	Total
Classification	Non oil palm	170	23	193
	Oil Palm	24	84	108
	Total	194	107	301
Combined input (OA = 90.3%) PA = 88.8%, UA = 86.7%, Kappa = 0.802		Reference Data		
		Non oil palm	Oil palm	Total
Classification	Non oil palm	178	14	192
	Oil Palm	17	111	128
	Total	195	125	320

3. Results and discussion

3.1. Comparison of different data input classifications

As expected, the combination of both datasets as inputs outperforms either dataset alone as an input, as the classifier can learn patterns unique to oil palm both from the spectral reflectance signature of Sentinel-2 and backscatter response of Sentinel-1 (Table 2). This confirms findings from similar previous studies in southeast Asia (Descals et al., 2019; Sarzynski et al., 2020), as well as Amoakoh et al. (2021), which mapped land cover with a focus on peatland but including oil palm in Ghana's southern coast using a similar method. The overall accuracy of the combined Sentinel-1 and Sentinel-2 classification was 90.3%, with an oil palm class user's accuracy of 86.7% and an oil palm class producer's accuracy of 88.8%. The Sentinel-2 only classification misclassified other green vegetation as oil palm due to their similar spectral responses, as has been found with the use of Landsat imagery in Indonesia (Sarzynski et al., 2020). The Sentinel-1 only classification misclassified urban areas as oil palm due to similar backscatter responses. Both horizontal and vertical structure influence backscatter, and irregularly planned cities like many of those across West Africa present differently than expected for urban areas, complicating classification (Blasco et al., 2020). As the study area included large areas of other green vegetation (green vegetation that is not natural forest or oil palm plantation), the Sentinel-2 only classification led to a large over classification of oil palm areas, especially smallholder areas (Table 2; Table 5).

Variable importance offers insight into the physical properties driving the random forest classification results (Table 3). Most important in the Sentinel-2 only classification were the two SWIR bands (B11 and B12), similar to the findings of Descals et al. (2019). The SWIR range of Sentinel-2 has been useful in differentiating tree types in other regions, due to its ability to detect variability in water content (Murakami, 2006; Abdi, 2019). The NIR band and NDVI, features closely related to greenness and vegetation health, also proved important. Shorter wavelength bands in the visible portion of the electromagnetic spectrum proved less useful. In the Sentinel-1 only classification, VH was the most important input variable. The structure of oil palm, specifically its cylindrical trunk, lack of branches, and blade-like leaves, gives it a characteristic backscatter that differs from other tree and vegetation types (Dobson et al., 1996; Miettinen et al., 2015). This unique canopy influences the volume scattering that dominates VH backscatter signals, resulting in VH and VH-VV being crucial to separating out oil palm from other land covers (Descals et al., 2019; Xu et al., 2021). RVI attains the second highest variable importance, with oil palm attaining a degree of separability from other vegetation classes with its relatively low RVI values. RVI has been found to relate closely to vegetation measures like leaf area index and biomass (Kumar et al., 2013). Oil palm had a very low RVI in the study area, possibly due to its unique leaf structure and lower biomass than natural forest. Variable importance in the combined classification yielded similar results, with RVI, VH, and SWIR proving important. However, the red edge 1 band (B5) of Sentinel-2 was found to be most important to this classification. As expected, the most important inputs were a mix of Sentinel-1 and Sentinel-2 features, indicating the usefulness of the combined data source approach.

For the combined input classification, the smallholder overall accuracy was 80.4%, with an oil palm class user's accuracy of 90.4% and an oil palm class producer's accuracy of 68.0% (Table 4). The low producer's accuracy points to errors of omission, and therefore an underestimate of smallholder areas. Descals et al. (2021) found their area estimates of oil palm to be much lower than expected, driven by the omission of smallholders. The high user's accuracy of the combined approach, however, means there is a high likelihood that a given pixel classified as oil palm is correct. This suggests that this combined classification gives an accurate, but conservative measure of oil palm over smallholder areas.

3.2. Area estimates of oil palm for study area

Pixel areas for the oil palm class were calculated for each of the classifications (Table 5). It is important to note that the Sentinel-1 data used in this study did not cover the entire study area of the 50-km buffer region around the selected oil palm mill at Kwae plantation (Fig. 4). Sentinel-1 scenes from only one path and frame were used to ensure constant view angle. The Sentinel-2 data covers the entirety of the study area, but only the overlapping region of Sentinel-1 scene and total study area was used for area calculations to allow for comparison. While overall areas show variation, the three classifications give relatively similar estimates of industrial oil palm area. The smallholder areas are the source of much of the variation between overall oil palm area estimates, caused by the more complex heterogeneous environment of land covers that cause misclassifications for the Sentinel-1 only classification (*i.e.*, urban areas) and the Sentinel-2 only classification (*i.e.*, other green vegetation). The postprocessing applied to the combined classification decreased the area greatly from what is shown in Table 5, resulting in 64,961 ha of oil palm in the study area. This suggests there were many pixels classified as oil palm in groups smaller than what is a reasonable minimum area for smallholder plots.

3.3. Comparison of classification output with available statistics and maps

A recertification document submitted to the RSPO on December 15, 2019 for Kwae and Okumaning plantations gave insight into industrial oil palm areas within the study area for the study period (SCS Global Services, 2019). It stated that there are 7268 ha of

Table 3
Variable importance for each classification.

Variable Importance Rank	Sentinel-1 only classification	Sentinel-2 only classification	Combined classification
1	VH	SWIR 1 (B11)	Red Edge 1 (B5)
2	RVI	SWIR 2 (B12)	RVI
3	VV/VH	NIR (B8)	VH
4	VV	NDVI	SWIR 1 (B11)
5	VV-VH	Blue (B2)	Red Edge 4 (B8A)

Table 4
Error matrix for smallholder accuracy assessment of combined classification.

Smallholder combined OA = 80.4% PA = 68.0% UA = 90.4% Kappa = 0.608		Reference Data		
		Non oil palm	Oil palm	Total
Classification	Non oil palm	116	40	126
	Oil Palm	9	85	94
	Total	125	125	250

Table 5
Area calculations for each classification in hectares (ha).

	Sentinel-1 only	Sentinel-2 only	Combined
Industrial area (ha)	8,109	7,892	8,328
Smallholder area (ha)	89,852	141,426	78,850
Total oil palm area (ha)	97,961	149,318	87,178
Percent industrial (%)	8.3	5.3	9.6

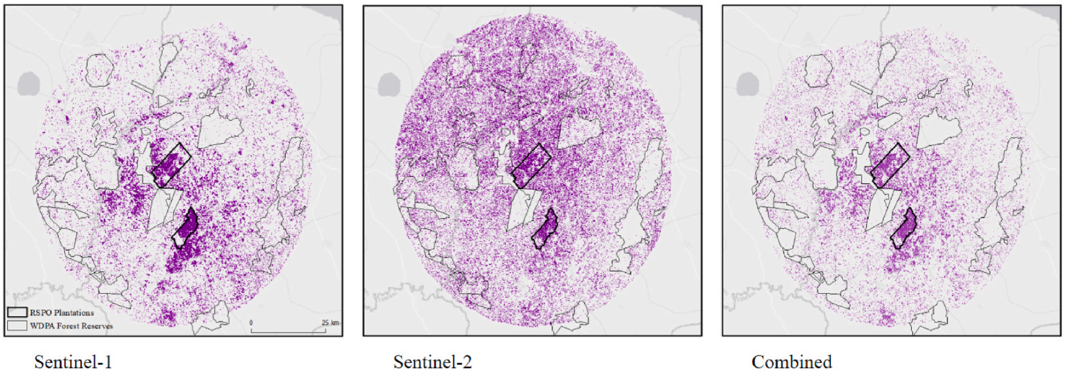

Fig. 4. Oil palm maps of study area for random forest classification with Sentinel-1 only inputs, Sentinel-2 only inputs, and combined inputs.

mature oil palm in the two plantations combined for 2019. Our combined result classified 8328 ha of mature, closed-canopy oil palm for the two industrial plantations. Remote sensing studies often underestimate oil palm area by excluding recently planted plantations (Descals et al., 2019) with varying ages of first detection for mature closed-canopy oil palm plantations ranging from 3 (Descals et al., 2019, 2021) to 8 years (Koh et al., 2011). The specific age cutoff for mature oil palm used in the reference document was not provided.

RSPO planting maps from 2014 (RSPO, 2014) allowed for spatial validation. Since the maps provide the planting year for each field

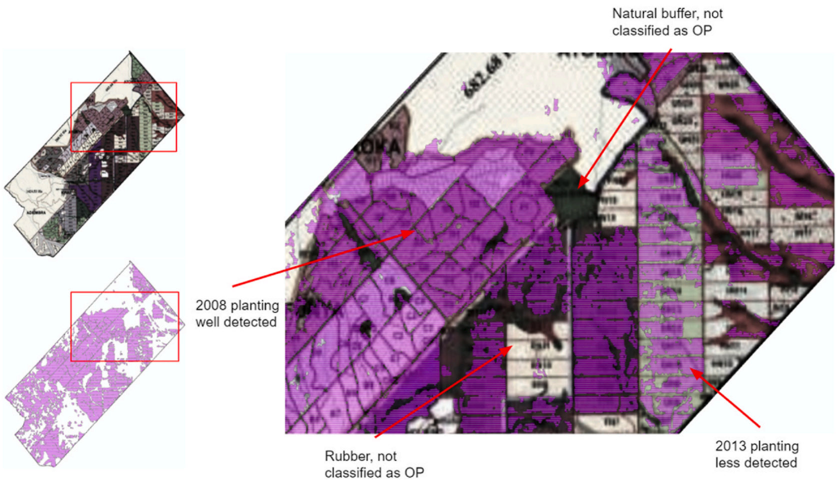

Fig. 5. 2019 combined classification result (postprocessed) overlaid on 2014 RSPO plantation map of Kwae plantation (northern focus area). Base map data source: RSPO (2014).

in Kwae and Okumaning industrial plantations, they can help determine the effectiveness of the classifier for mapping oil palm of different ages. A visual analysis of Kwae plantation suggested the classification performs well, correctly classifying fields planted with oil palm and avoiding misclassifying rubber fields as oil palm (Fig. 5). Additionally, plantation infrastructure like buildings and roads were not classified as oil palm, nor were RSPO-required natural buffer areas. Fields planted in 2013 appear to only be partially detected, potentially due to a lack of the full canopy development that is necessary for the spectral and backscatter signals that make oil palm unique by the 2019 study period (Koh et al., 2011; Descals et al., 2019, 2021; Charters et al., 2019). Separate training data representative of the young oil palm class would have to be collected to properly map this class (Li et al., 2015).

A challenge in using planting maps from 2014 is that older oil palm fields may have been replanted by the 2019 study period. Fig. 6 shows oil palm fields planted in 1985 that were still there in the 2014 planting map, however our classification did not detect them. It is known that oil palms have 20–30 year economic lifespans, after which yields decrease and they are often replanted (Pashkevich et al., 2020). Further investigation using the Hansen forest cover loss product confirms that these fields were replanted, with tree cover loss detected in 2015. Additionally, a region listed as unplanted in 2014 was filled with small plots as of 2019, correctly classified by our combined classification and supported by the Hansen forest cover loss data and analysis of high-resolution imagery (Fig. 6).

The results of Descals et al. (2021) were similar to FAO statistics for countries in southeast Asia with large industrial oil palm areas, but greatly underestimated oil palm areas in West Africa, suggesting an undercounting of smallholder areas. Their method maps only 48,249 ha of oil palm in all of Ghana, less than 14% of the area reported by the FAO for 2019. Therefore, the Descals product cannot be taken as an accurate map to validate our results and instead offers an opportunity to show our local improvements to their global map. The Descals product mapped 6735 ha of industrial oil palm following our previously established definition, compared to our 8328 ha. While the true amount of industrial oil palm between Kwae and Okumaning plantation is unknown, our classification did achieve a 90.3% overall accuracy for these plantations, and visual interpretation of high-resolution imagery and RSPO planting maps shows clear portions of oil palm in Kwae plantation missed by the Descals classification and correctly classified by our method (Fig. 7a). The Descals product mapped only 12,617 ha of smallholder oil palm within the study area, while our combined classification mapped 56, 633 ha (after postprocessing explained in Section 3.2). Our independent smallholder accuracy assessment provides confidence that our smallholder mapping results outperform Descals in an area of known difficulty for them, highlighting the underestimation of their product. There are almost no areas where smallholders were detected by the Descals product and not by our combined classification, as can be seen in an area of known high smallholder density (Fig. 7b).

4. Conclusions

This research supports the findings of studies in other regions that the combined use of SAR and multispectral data outperforms either alone for classification of oil palm. Classification was driven by the unique structure of oil palms, seen in the importance of VH backscatter and RVI, as well as their spectral reflectance in the red to SWIR portions of the electromagnetic spectrum. In using only publicly available data sources, no field data, and the GEE platform, this approach can be quickly and freely adapted for anywhere on Earth. While this study used C-band SAR data from Sentinel-1, the deeper penetrating power of L-band data from the upcoming NISAR Mission offers exciting future work for this field.

These results provide a high-resolution, high-accuracy map of mature, closed-canopy oil palm in 2019 to aid in environmental and economic decision-making for one of the most important production areas in Ghana. These results update outdated RSPO planting maps, supplement the limited RSPO certified plantation shapefiles, and improve upon the results of a global oil palm map locally, greatly enhancing the information publicly available about oil palm within the study areas. The focus on effectively mapping smallholders is of particular importance for Ghana, as it has a smallholder driven oil palm sector and the yields of these smallholders are comparatively low (Osei-Amponsah et al., 2012; Khatun et al., 2020). Better understanding of where these smallholders are can allow for policies to be enacted that allow for higher yields, bringing more into sustainable certification and reducing the expansion of oil palm at the expense of Ghana's remaining natural forests.

Ethical statement

All ethical practices have been followed in relation to the development, writing, and publication of the article, following the Elsevier ethics in publishing guidelines.

CRediT author statement

Jacob Abramowitz: Conceptualization, Methodology, Software, Validation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing, Visualization. **Emil Cherrington**: Conceptualization, Writing – Review & Editing, Supervision. **Robert Griffin**: Conceptualization, Writing – Review & Editing, Supervision, Funding Acquisition. **Rebekke Muench**: Conceptualization, Supervision. **Foster Mensah**: Conceptualization, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

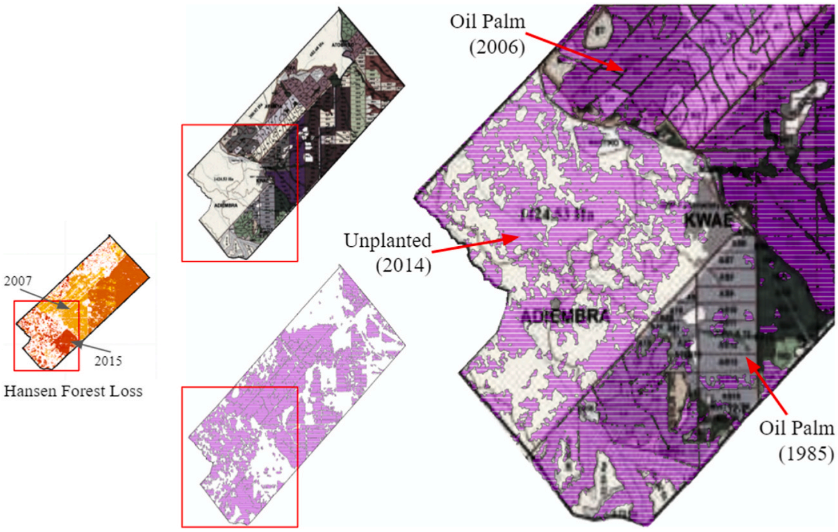

Fig. 6. 2019 combined classification result (postprocessed) overlaid on 2014 RSPO plantation map of Kwae plantation (southern focus area). Base map data source: RSPO (2014).

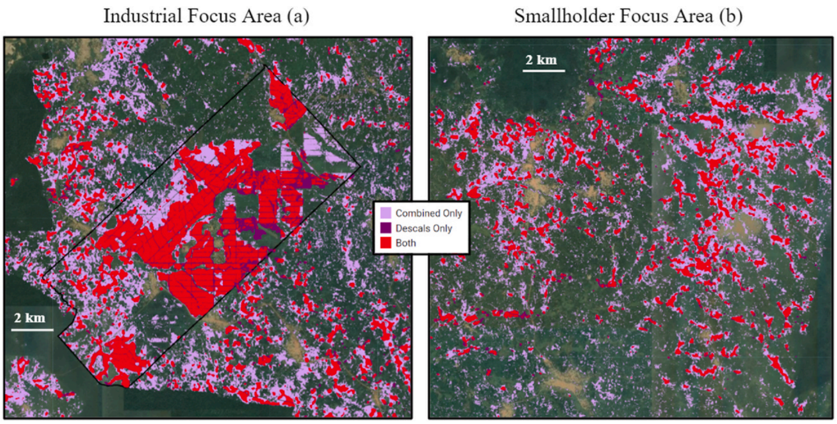

Fig. 7. Comparison of Descals oil palm classification and our combined classification over industrial (Kwae) and smallholder focus areas. Basemap data source: Google Imagery, CNES/Airbus, Landsat/Copernicus, Maxar Technologies.

Data availability

Data will be made available on request.

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Appendix

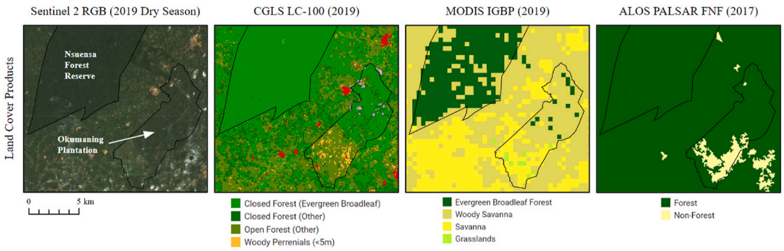

Fig. A.1. Common land cover products over a forest reserve and industrial oil palm plantation in Ghana study area.

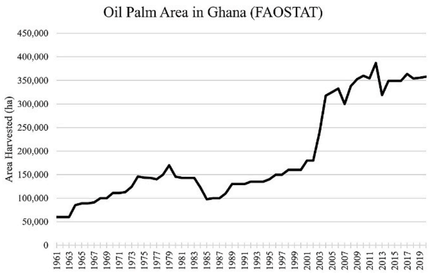

Fig. A.2. Oil palm cultivated area in Ghana, 1961–2020. Data source: FAOSTAT, UN FAO.

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