Deforestation, plantation-related land cover dynamics and oil palm age-structure change during 1990–2020 in Riau Province, Indonesia

Izaya Numata¹², Andrew J Elmore¹, Mark A Cochrane¹, Cangjiao Wang³, Jing Zhao¹ and Xin Zhang¹

¹ Appalachian Laboratory, University of Maryland Center for Environmental Science, Frostburg, MD, United States of America
² Geospatial Sciences Center for Excellence, South Dakota State University, Brookings, SD, United States of America
³ School of Environmental Science and Spatial Informatics, China University of Mining and Technology, Xuzhou, China

* Author to whom any correspondence should be addressed.
E-mail: izaya.numata@sdstate.edu

Keywords: oil palm, forest, Indonesia, land cover land use change

Abstract
The expansion of plantations, such as oil palm, in Indonesia has caused large-scale deforestation. Loss of tropical forest, in particular peatland forest, is a major ecological and environmental threat as well as a source of atmospheric carbon emissions. Understanding the spatio-temporal dynamics of plantation expansion may illuminate pathways to reduce deforestation while maintaining high yields in existing plantations. Beyond mapping forest conversion to plantations, it is also important to understand post-conversion plantation success and crop age. In the case of oil palm, the typical productive lifespan is 25–30 years before replanting or conversion to other land use becomes necessary. Knowledge about the extent of oil palm in different productive growth stages is important for yield estimation and improving management strategies. This study characterizes the land-cover and land-use changes inherent to oil palm plantation expansion and age-structured oil palm dynamics across Riau, the province with the greatest production of oil palm in Indonesia, using a 30 year time-series of Landsat satellite imagery. From 1990 to 2020, Riau lost 4.63 M ha of forest, while oil palm extent grew six-fold, reaching an estimated 3.52 M ha in 2020. Rapid expansion of oil palm plantations in Riau resulted in the predominance of younger age classes (<10 yr-old) and rapidly increasing yields during 2010–2020. Conversion dynamics changed over time such that, after 2014, the <10 yr age class declined by 14%, whereas the 10–20 yr-old (peak yield stage) and ≥20 yr-old (decline stage) age classes increased by 11% and 3%, respectively. In 28 years of observation (1992–2020), 41% of oil palm planted between 1990 and 1992 underwent at least one cycle of replanting in Riau.

1. Introduction

Oil palm plantations in Southeast Asia have expanded rapidly in recent decades due to global demand for vegetable oil products. Oil palm extent increased from 0.3 million ha (M ha) in 1980 to 14.3 M ha in 2018 (Ministry of Agriculture of Indonesia 2020). Indonesia now has the greatest area of oil palm plantations and palm oil production in the world (Vijay et al 2016, Descals et al 2021). Environmental impacts of oil palm plantations have been reported in Indonesia as well as other palm oil producer countries (Meijaard et al 2020). Nearly 10 M ha (11%) of forest area was lost between 2000 and 2019 due to land cover land use change (LCLUCs) (Gaveau et al 2022). Forests comprised 44% of Indonesia’s landmass in 2019, but the regional amounts of forest remaining vary from 25% in Sumatra to nearly 50% in Kalimantan (Gaveau et al 2022). In recent decades, oil palm plantations have progressively expanded into more marginal lands, including peatlands, where fires associated with expansion have caused large losses of soil carbon to the atmosphere (Ramidami and Hino 2013).
In depth analyses of particular regions within Indonesia have the potential to reveal land use and land cover change processes, associated impacts, and address questions of oil palm sustainability. Riau province (Figure 1), for example, has a long history of oil palm plantations and is the largest producer of palm oil, accounting for one fifth of Indonesia's national production (Ministry of Agriculture Indonesia 2020). Expansion of the palm oil industry has resulted in dramatic economic growth, in Riau, improving life quality for producers, especially smallholders (Apresian et al 2020), but at the cost of serious environmental degradation in recent decades. Forestlands in Riau declined by more than 60% between 1990 and 2013 and deforestation rates have continued to grow, even in recent years (Rehman et al 2015). The impacts of forest conversion to plantations are particularly serious in peatlands, which are recognized as biodiversity hotspots with extensive carbon storage (Randami and Hino 2013).  

In response to global pressures on practices of the oil palm industry in Southeast Asia, the Indonesian government has implemented sustainability policies such as the Indonesian Sustainable Palm Oil standard, the 2011 Moratorium on deforestation on primary forest and peatland, and the 2018 Moratorium on palm oil plantation permits (Saputra and Sail 2018). These policies promote sustainable oil palm plantations, reduced forest loss through restricting deforestation, and encourage oil palm producers in Indonesia to shift plantation expansion from replacing forest to development on non-forest areas (Austin et al 2017). This issue is more serious in those regions, like Riau, where the supply of forests to be converted into oil palm has nearly been exhausted.

There are many studies reporting forest conversion to oil palm and other human land use in Indonesia, but post-deforestation oil palm dynamics are not well studied. The oil palm life cycle lasts 25–30 years and includes three basic growth stages. Oil palm trees yield little palm oil over the first several years, achieve highest yields when between 8 and 20 years old, and experience declining productivity thereafter (Ismail and Mamat 2002). Replanting typically occurs after 25–30 years (Ismail and Mamat 2002, Ahouoloupe et al 2013), although some unproductive oil palm is replanted much earlier. Thus, maintaining oil palm in all growth stages, and replanting aging or unproductive oil palm, influences oil palm age structure and regional productivity, and can be a sustainable strategy to maintain oil palm yields without further deforestation. Despite the importance of the oil palm life cycle on yields, Indonesia holds a large amount of oil palm greater than 25 years old, which makes Indonesian palm oil productivity much lower than its potential levels, and lower than in comparable countries such as Malaysia (Ardana et al 2022). In this context, spatial and temporal information on the oil palm productive growing stages and age structure of oil palm plantations across large areas is critically important for estimating potential palm oil production and helps efforts to build sustainable management strategies (e.g. proper timing for replanting). Periods of rapid oil palm expansion have important impacts on oil palm age structure and productivity, but quantifying these effects requires detailed information on (a) the relative timing of deforestation and initial oil palm planting, (b) the longevity of oil palm plantations, and (c) the timing of oil palm re-planting. Data on these landscape dynamics has not been well addressed by recent analyses. Remote sensing data has been instrumental in mapping oil palm stand ages in Southeast Asia (Fitrianto et al 2018, Danylo et al 2021). However, these studies provide single year oil palm age maps and have not addressed spatial and temporal dynamics of age structure as a function land cover change in Indonesia. In this study, we characterize the land-cover and land-use changes (LCLUCs) inherent to plantation expansion and age-structured oil palm dynamics based upon a 30 year time series of land cover maps. We focus the work on Riau, Indonesia, where tracking spatial and temporal patterns of forest loss, oil palm plantation, and resulting oil palm age structure will provide insights for future sustainable management of oil palm. More specifically, a detailed map of oil palm age will allow to identify places of over-aged plantations to target for yield improvement as replanting old and unproductive oil palm will be critical to increase yield given the land scarcity and recent environmental regulations that limit deforestation for further expansion of oil palm in this country. National-scale analyses of oil palm expansion in Indonesia are available that provide general trends of spatial and temporal dynamics of LCLUC, but do not provide the level of detail necessary to understand oil palm age structure. For these analyses, Landsat satellite imagery was used to create land cover maps for every other year from 1990 to 2020. Observed land cover changes were used to estimate the timing, location and extent of oil palm, and to generate oil palm age maps.

2. Materials and methods

2.1. Study area

Riau Province (87 023 km²) in central-east Sumatra, Indonesia (0° 32′0″N, 101° 27′0″E) (Figure 1) receives an average rainfall of 2300 mm and has an average temperature of 27 °C (Ministry of Agriculture Indonesia, 1998–2018). The natural vegetation type is lowland rainforest, with approximately 30% on peatlands (Ritung et al 2011). Riau’s tropical forests were selectively logged in the 1970s and have been progressively converted to oil palm plantations since the mid-1980s. According to government statistics, in 2019, Riau had 2.74 M ha of oil palm plantations, 20% of the total area in Indonesia (Ministry of Agriculture,
Indonesia [2020]). Nearly 65% of oil palm cultivated in Riau is owned by smallholders and the rest by state-owned enterprise (<3%) or private industry (33%) (Ministry of Agriculture, Indonesia [2020]). Besides oil palm, pulpwood plantation (Acacia and Eucalyptus) is a major contributor to the region’s economy. Other agricultural crops such as coconut, rubber and coffee occupy relatively small areas in Riau (Ministry of Agriculture, Indonesia [2020]).

2.2. Landsat data and preprocessing
All available surface reflectance products of Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (Operational Land Imager - OLI) data from nine scenes covering the study area from 1990 to 2020, totaling 8395 individual images, were processed for land cover mapping. Data processing was carried out using Google Earth Engine (GEE, Gorelick et al [2017]).

All visible, near infrared, and shortwave-infrared bands were used for calculation of Vegetation Indices and spectral mixture analysis endmember fractions as input variables for land cover classification. In preprocessing, pixels identified as cloud, cloud shadow, or water were masked out using data from the pixel_qa layer. These cloud screening flags were generated using the Fmask algorithm (Zhu et al [2015]). Landsat 5, 7 and 8 reflectance data were cross-calibrated using the method of Roy et al [2016] to correct for sensor differences and generate a consistent, harmonized dataset. Due to high amounts of annual cloud cover, typical even in the dry season of our study area, we found that single year-Landsat composites could not reliably fill all missing pixels for every year of the study period. Therefore, we created bi-annual Landsat composites by applying a median temporal filter to all cloud-free observations within the 1990–2020 period.

2.3. Spectral index calculation and image compositing
We derived several input variables from each Landsat image for land cover classification (table S1). First,
we used linear spectral mixture analysis to unmix spectral signatures of each pixel into four fractions, including green vegetation (GV), non-photosynthetic vegetation (NPV), soil, and shade. Endmembers for GV, NPV, and Soil were selected by first identifying endmember candidates from a clear sky Landsat image using the Sequential Maximum Angle Convex Cone tool available in ENVI 5.3. Then, final endmembers were determined based upon the spectral shape, image context and root mean squared errors of the resulting fraction images following Numata et al (2007). These endmembers were then used to calculate GV, NPV, Soil and Shade fractions for each pixel in each image using the image.unmix() function in GEE. Using endmember fractions, the normalized difference fraction index (NDFI) was used as an indicator of forest canopy structure. This index has previously been applied to monitor forest loss and degradation in the Amazon and forest canopy cover change in West Africa (Souza et al 2005, Souza Jr et al 2013, Bullock et al 2020, Wimberly et al 2021).

We also calculated several additional spectral indices commonly used for forest mapping, including the normalized difference vegetation index (Tucker 1979), enhanced vegetation index (Jiang et al 2008), normalized burn ratio (López García and Caselles 1991), and the normalized difference water index (Gao 1996). Finally, we calculated standard deviations of these predictor variables from the stack of each bi-annual image datasets to be included in the random forest (RF) classification model. The final data set included 27 predictor variables.

2.4. Landcover mapping

We considered nine classes in our land cover map (figure 2 and table 1). Oil palm was divided into mature (>4 year-old) and young (1–4 year-old) classes. The satellite-based land cover map of the Ministry of Environment and Forestry of Indonesia has six forest types in Riau, comprised of primary forest (dry land, mangrove and swamp) and secondary forest (dry land, mangrove and swamp). We combined all these classes as a single ‘forest’ class for simplicity. We collected reference and validation samples for these land cover classes from very-high resolution imagery obtained through Google Earth. In total, 1508 sample units were randomly collected from the study region with dates between 2017 and 2018 for training the land cover model.

We used the RF regression algorithm (Breiman 2001), a tree-based ensemble machine learning algorithm, for land cover classification. The RF algorithm generates predictions from a set of explanatory variables by creating a set of regression trees and aggregating their results to improve prediction accuracy. We extracted the Landsat spectral indices from corresponding training samples and years in the training dataset. We ran the RF regression model using the smileRandomForest() function in GEE with an ensemble size of 100 trees, a bag fraction of 0.56, variables per split equal to the square root of the number of predictor variables, and a minimum node size of one. We then applied this RF model to map land cover classes across the entire study area for all years from 1990 to 2020.
Table 1. Land cover classes in Riau.

| Class         | Description                                                                 |
|---------------|-----------------------------------------------------------------------------|
| Mature oil palm | Oil palm plantation with high canopy closure (>4 years old)                 |
| Young oil palm | Oil palm plantation with open canopy (1–4 years old)                        |
| Open dry land  | Other land use types including open area, crops and pasture                 |
| Forest         | Natural forest                                                               |
| Bare soil/Impervious | Bare ground after deforestation and replacement of oil palm trees and crop harvest. Impervious surface such as urban area, roads and other constructions |
| Other vegetation | Coconut palm, grass, vegetation in riparian zone, rubber trees, recovery and other unknown vegetation surfaces |
| Pulpwood      | *Acacia* and *Eucalypt*                                                     |
| Water\(^b\)    | Water body                                                                  |

\(^a\) Land cover class introduced to land cover map after temporal filtering.

\(^b\) Water assigned by JRC Global Surface Water data (https://global-surface-water.appspot.com).

As a post-classification correction, we adopted temporal filtering transition rules to correct disallowed land cover transitions along a series of consecutive years within the 1990–2020 time period. The detailed description of post-classification correction is found in the supplementary material (SM). We used a validation dataset (624 samples) from high-resolution imagery for accuracy assessments of our land cover maps. Overall land cover map accuracy of the seven land covers was 86.3%. See SM for more details.

2.5. Forest losses and oil palm expansion from 1990 to 2020

We quantified bi-annual forest loss from 1990 to 2020. In addition, we quantified newly added oil palm and other land cover types including pulpwood, open dry land and other vegetation within deforested areas, but noted the number of years between initial deforestation and subsequent detection as a new land cover type. We generated maps that record the years of change for forest loss, oil palm expansion land cover change from the time series of land cover maps (figures 3(a)–(c)). To quantify changes, first we created bi-annual maps of forest-non-forest, oil palm-non-oil palm and pulpwood-non-pulpwood, separately. Differences in area between two consecutive time periods, say \( t_1 \) and \( t_2 \), indicated changes in respective land cover types during the interval. Oil palm and pulpwood plantations undergoing periodic harvest and/or tree replacement were not considered ‘expansion’ for these intervals to avoid double counting within these classes. We analyzed landscape dynamics across Riau province and investigated if differences existed between areas on or off peatlands.

2.6. Oil palm age map and age structure

To understand oil palm age structure and its change over time in Riau, we developed oil palm age maps for every two years of the 2010–2020 period and identified oil palm with ages 20 years old or older in each oil palm map for these years. Oil palm age maps were developed by overlapping oil palm and non-oil palm maps along sequential time periods. Age counting starts with the first appearance of young oil palm after the last change caused by deforestation, oil palm replacement, or land cover conversion from non-oil palm. When oil palm is cut and replanted, oil palm age starts over at zero years if the land cover is bare soil or two years if the next observed land cover is ‘young oil palm’.

From a palm oil yield perspective, oil palm lifespan can be divided into three stages defined by Alam et al. (2015): Immature (rapid increase), prime (peak yields) and old (yield decline). Oil palm age is directly related to palm oil yield and used to indicate
yield growth stages, its lifespan and optimal timing of replacement or rotation (Ismail and Mamat 2002, Aholoukpe et al. 2013, Alam et al. 2015). Oil palm ages in each map were divided into three categories: Step 1—rapid increase (<10 yr-old), Step 2—peak yields (10–20 yr-old), and Step 3—decline (>20 yr-old or older). The oil palm age maps provided landscape-level oil palm age structure at each time period.

To illustrate oil palm replanting time, we performed a cohort analysis of oil palm planted in 1990–1992 to track oil palm age structure change from 1992 to 2020 bi-annually, based upon the time series of oil palm age maps.

3. Results

3.1. Forest loss and expansion of plantations in Riau (1990–2020)

Substantial land cover change has occurred in Riau during the thirty years since 1990, with deforestation and oil palm expansion comprising major components (figures 4 and 5). In 1990, forest covered 70.8% of Riau province, while oil palm occupied only 6.4% (table 2). By 2020, forest area was reduced by over 74%, covering only 18% of Riau. Forest loss rates were greatest from 1990 to 2000, averaging 0.21 M ha yr$^{-1}$, followed by 0.18 M ha yr$^{-1}$ from 2000 to 2010, but deforestation rates slowed substantially between 2010 and 2020, averaging 0.08 M ha yr$^{-1}$. Since 2000, more forest clearing has occurred on peat than mineral soils. Whereas in the 1990s, <34% of deforestation occurred on peatlands, the proportion of clearing occurring on peat has grown to ~63% in the last decade.

Oil palm plantation area expanded 5.5-fold since 1990 to cover 41% of Riau in 2020. The expansion rates accelerated each decade, with conversions of 0.077, 0.088 and 0.142 M ha yr$^{-1}$ during the 90s, 00s and since 2010, respectively. Although the majority of oil palm continues to be on mineral soils (71%), expansion onto peatlands has accelerated. The proportion of oil palm existing on peatlands grew from 9% in 1990, to 29% as of 2020. More than half (60%) of oil palm expansion into peatland forest has occurred since 2010.

Open dry land and pulpwood increased in area while ‘other vegetation’ remained constant throughout the study period. Open dry land area increased from 0.91 M ha in 1990 to 2.71 M ha in 2010, then started declining gradually to below 2.0 M ha in 2018, with a small recovery in 2020. Pulpwood plantations expanded in area at a rapid rate since 1990, increasing by over 860% by 2020, with 77% of the expansion occurring since 2000. While 25% of these plantations were on peat in 1990, the proportion grew to over 57% by 2020. In 1990, pulpwood covered less than 1% of Riau but, as of 2020, the proportion had grown to nearly 10%.

The expansion of plantations accounted for 62% (45% and 17% for oil palm and pulpwood, respectively) of the total deforested area during the 1990–2020 period. The rest of forest losses were related to other land cover types such as open dry land (29%) and other vegetation (6%). After 2010, however, the majority of oil palm expansion was related to the loss of open dry land rather than the loss of forest.

3.2. Oil palm age structure change and rotation

Figures 6(a) and (b) illustrate the map of oil palm with ages varying from 2 yr-old to >30 yr-old in 2020. Oil palm ages can be verified with temporal changes of greenness (NDFI) of oil palm shown in figure S2. Age structure changes of oil palm with three growth stages and annual palm oil production (Ministry of Agriculture, Indonesia) over the 2010–2020 period are shown in figures 6(c) and (d). While the total area of oil palm plantations and palm oil production have progressively increased, oil palm age structure gradually changed between 2010 and 2020 in Riau. Across the study period, the area of the
Figure 5. Total area of land cover classes: forest, oil palm, open dry land, pulpwood and other vegetation in Riau (a) and within Riau’s peatland (b) during 1990–2020.

|                | 1990   | 2000   | 2010   | 2020   |
|----------------|--------|--------|--------|--------|
| Forest         | 6.28   | 4.20   | 2.43   | 1.65   |
| Overall coverage| 68.5% | 45.8%  | 26.5%  | 18.0%  |
| Mineral Soil   | 3.03 (48%) | 1.65 (39%) | 0.88 (36%) | 0.58 (35%) |
| Peatland       | 3.25 (52%) | 2.55 (61%) | 1.55 (64%) | 1.07 (65%) |
| Oil Palm       | 0.59   | 1.21   | 2.06   | 3.52   |
| Overall coverage| 6.4%  | 13.1%  | 22.5%  | 38.4%  |
| Mineral Soil   | 0.063 (91%) | 1.22 (84%) | 1.87 (80%) | 2.68 (71%) |
| Peatland       | 0.06 (9%)  | 0.24 (16%) | 0.47 (20%) | 1.08 (29%) |

Note: Numbers in parentheses are proportions of each land cover type on mineral soil and peatland in Riau.

Figure 6. (a) Oil palm age map of Riau in 2020, (b) a zoomed area of oil palm age map, (c) changes in oil palm age structure with three age classes in area and annual palm oil production (orange line) and (d) in percentage from 2010 to 2020.
rapid increase class (<10 yr-old) expanded from 2010 to 2014 and then gradually decreased towards 2020 (figure 7(c)). Overall, this age class (figure 7(d)) declined from 60% to 47% between 2010 and 2020. The other age classes, peak yield (10–20 yr-old) and decline (>20 yr-old), made up smaller proportions of the landscape, 30%–37% and 11%–17%, respectively. However, the proportions of these classes had trends opposite of the young age class, decreasing from 2010 to 2014 and increasing thereafter.

We tracked age structure changes within the planted area of the 1990–1992 oil palm cohort (146 000 ha) to examine rotation timing of long-lived oil palm (figure 7). Some areas were converted from oil palm into other land cover types during the study period but reconverted to oil palm in later years. In 2006, 14 years after plantation, 8% of oil palm planted in 1992 had been replanted. Twenty years after planting, 44% of oil palm trees had been either replanted (20%) or converted to other land uses (23%). By 2020, 41% had been replanted, with half replanted after 2014 (i.e. rotation times ranging from 22 to 28 years). The remaining 43% has not been replanted since its first planting. This majority of very old oil palm is found in industrial oil palm plantations (figure S3). The consistent high greenness (NDVI) of oil palm throughout the 30 year period (figure S3), as well as the continued presence of mature oil palm on the satellite images from 1990 to 2020 (figure S4) validate the existence of such old oil palm.

4. Discussion

4.1. Forest conversion to oil palm and its potential future scenarios in Riau

During the past three decades, Riau lost 4.63 M ha of forest. As of 2020, forest accounts for only 18% of its territory, much lower than the 44% in Indonesia at the national level in 2019 (Gaveau et al 2022). This indicates that there is limited opportunity for future deforestation and oil palm expansion in Riau compared with other regions in Indonesia. Therefore, the recent observed decline in deforestation rates can only partly be attributed to policy efforts, such as the moratoriums on deforestation and issuing of new permits for oil palm expansion in primary forests in 2011 and 2018, and the Roundtable on Sustainable Palm Oil certification system (Carlson et al 2018, Austin et al 2017, Lee et al 2020). Additionally, a recent decline in the price of palm oil may have slowed oil palm expansion (Gaveau et al 2022). Nevertheless, our results demonstrate that oil palm expansion has continued at the expense of open dry land and pulpwood, despite decreasing deforestation rates since 2010 (figure 5). Clearly, new oil palm plantations have been increasingly established in areas that were previously deforested for other land uses. A similar trend was observed by Austin et al (2017), who reported an increase in the proportion of plantations derived from non-forest land from 22.1% during 1995–2000 to 38% in the 2010–2015 period. Under the conditions of global pressures, government
restrictions, and growing scarcity of forestland, the expansion of oil palm plantations in Riau will progressively become more limited, likely causing the palm oil industry to adopt more intensive production systems to maintain or increase production in existing plantation areas. This would follow a globally observed land use transition pattern from expansion of land use by frontier clearings to intensification of agriculture production systems (Foley et al 2005). While Indonesia remains the world’s largest palm oil producer, the bulk of future expansion of the global oil palm estate is likely to be concentrated in new producer countries in Africa and South America (Qaim et al 2020).

However, the future of remaining forest in Indonesia is still unknown as the end of the 2018 Moratorium in late 2021 poses a new threat of deforestation for oil palm plantation (Saputra and Saif 2018). This would be a more serious conservation and environmental consequences in Riau where 65% of remaining forest are located in peatlands, which are highly valued for biodiversity and carbon sequestration. Recent expansion of oil palm plantations into peatlands appears to be related to forest conversion to smallholder oil palm plantations driven by worsening scarcities of suitable lands on mineral soils (Schoneveld et al 2019). According to Zhao et al (2022), 13% of remaining peat swamp forest in Riau are at high risk of being converted into smallholder oil palm due to close proximity to roads, mills, or both. From an environmental perspective, one of the implications of deforestation of peat swamp forest is increasing greenhouse gas emissions. Ramdani and Hino (2013) found that during the 2000–2012 period, CO2 emitted from peatland conversion accounted for 70% of the total CO2 emissions, more than double of the CO2 emitted from converted forests, i.e. 28%, in Riau. If peatland conservation continues, carbon emissions will be even greater and biodiversity loss will be more serious in Riau in the future.

4.2. Age-structured oil palm dynamics

Oil palm stand age is directly related to palm oil production and maintaining a distribution of oil palms in different growing stages through replanting aging oil palm trees as yields decline is critical for the sustainability of the palm oil industry in Indonesia and elsewhere.

Replanting aging oil palm trees has become an increasingly critical issue for sustaining production from oil palm plantations in Indonesia as the amount of oil palm older than 25 years old has grown to 2.4 million ha, mostly held by smallholders (Nurfatriani et al 2019). Aging oil palm is one of main factors (e.g. low seed quality and fertilization) behind the relatively-low productivity of Indonesian oil palms, which may lead to more deforestation for new or expanded plantations among smallholders (Ardana et al 2022). To promote oil palm replanting, the Indonesia government launched the Smallholders Replanting Programme (PSR) in 2017. The program provides financial support for smallholders to replant oil palm trees older than 25 years, aiming to increase productivity and promote sustainable management practices in oil palm plantations. However, the implementation of this program has been slow with unsuccessful outcomes so far (Ardana et al 2022).

In Riau, we found that old oil palm (≥25 yr) makes up just 8% of the total planted area in 2020. However, given the current trend of limited oil palm expansion and the slow replanting rate (figure 7), this amount will reach nearly 30% within the next decade, 2020–2030, if no additional expansion or replacement of oil palm occurs. Aging oil palm is already a serious issue for some districts in Riau province such as Kamper Regency where the majority of smallholder oil palm are older than 25 years old (Erwinda et al 2021).

Replanting old oil palm at an increasing rate will be critical for establishing a balanced age structured among oil palm plantations with sustained production levels, especially future oil palm expansion is limited. Based upon the 2010–2020 oil palm age maps, we observed age structure changes of oil palm, with a notable decline in the area of young oil palm age (i.e. <10 yr-old), with a concomitant increase in the areas of oil palm in the peak yield class (10–20 yr-old) and the old oil palm class (≥25 yr-old) after 2014. While this increase of peak productivity oil palm will enhance palm oil yield in the short term, if this trend persists, 50% of oil palm trees in Riau will be over 20 years old in 2030 and overall palm oil yield in this region will eventually decline unless older oil palm is replanted in a more timely fashion.

Remote sensing-based oil palm age maps, with information about the extent and stand age of oil palm trees, are useful for yield estimation (Tan 2013, Danylo et al 2021) and enable detection of replanting timing for oil palm trees (Nurrochmat et al 2019). Although the government report the total area of planted oil palm annually, age-related structural information is poorly described, with two main classes ‘immature’ and ‘mature’. Such information is useful for general knowledge on oil palm extent/expansion and its change over time in Indonesia, but spatially explicit oil palm ages would be more useful information for yield estimation, as well as for identifying where older oil palm should be replanted. Data on oil palm stand age will be necessary for regularly monitoring dynamics of aging oil palm in support of government efforts like PSR in Indonesia. This capability will also be required in other oil palm producing countries as their palm oil industries expand and mature.

From the perspective of vegetation monitoring, the information on the detailed age structure of plantations can also help to better interpret vegetation change (gain and loss) in global forest datasets such
as the Hansen et al (2013) where tree is any plant >6 m for Indonesia. As the area of oil palm plantations is much larger than forest in Riau, oil palm plantation dynamics may account for a significant portion of vegetation changes presented by these maps.

5. Conclusions

Over the past 30 years in Riau, Indonesia, 45% of deforested land was planted with oil palm (2.08 M ha). We also found that the majority of oil palm is planted on mineral soils, but oil palm expansion has increasingly occurred on Riau’s peatlands, where 65% of remaining forests are found. This worsening threat to remaining forests in peatlands, with high carbon contents, could disproportionately contribute to climate change if deforested. In terms of areas of planted oil palm in Riau, we also noted an age structure change since 2014, driven by recent decreases in new oil palm planting rates. This suggests that production per unit area of oil palm will begin declining, potentially spurring new deforestation in coming years if total yields are to be maintained. Given the recent trend of limited oil palm expansion in Indonesia due to policy efforts, lower oil prices and land scarcities, sustainable management of existing oil palm is necessary to maintain reasonable yield levels over time. We have shown that there is a substantial amount of increasingly senescent oil palm that could be replanted in the near future to sustain current production levels. Information on landscape structure of oil palm ages at regional scales provides needed data that can inform management strategies aimed at maintaining palm oil production rates through timely replanting.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgment

This project is supported by NASA LCLUC Fund (80NSSC20K0365).

References

Aholoukpe H, Bernard D, Flori A, Deleporte P, Amadji G, Chotte J L and Blavet D 2013 Estimating aboveground biomass of oil palm: algometric equations for estimating frond biomass For. Ecol. Manage. 292 122–9
Alam A S A H, Er A C and Begum H 2015 Malaysian oil palm industry: prospect and problem J. Food Agric. Environ. 13 143–8
Aresian S R, Tyson A, Varkkey H, Cohiruzzad S A B and Indraswari R 2020 Nusantara Int. J. Humanit. Soc. Sci. 2 1–29
Ardana I K, Wulandari S and Hartani R S 2022 Urgency to accelerate replanting of Indonesian oil palm: A review of the role of seed institutions IOP Conf. Ser.: Earth Environ. Sci. 974 012104
Austin K G, Monshier A, McCallum I, Fritz S and Kasibhatla P S 2017 Shifting patterns of oil palm driven deforestation in Indonesia and implications for zero-deforestation commitments Land Use Policy 69 41–48
Breiman L 2001 Random forests Mach. Learn. 45 5–32
Bullock F L, Woodcock C E and Olofsson P 2020 Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis Remote Sens. Environ. 238 110968
Carlson K M, Heilmayr R, Gibbs H K, Nooijipady P, Burns D N, Morton D C, Walker N F, Paoli G D and Kremen C 2018 Effect of oil palm sustainability certification on deforestation and fire in Indonesia Proc. Nat Acad. Sci 115 121–6
Danylo O, Pirker J, Lemoine G, Ceccherini G, See L, McCallum I H, Krasner F, Achard F and Fritz S 2021 A map of the extent and year of detection of oil palm plantations in Indonesia, Malaysia and Thailand Sci. Data 8 96
Descals A, Wich S, Meijaard E, Gaveau D I A, Peedell S and Szantol Z 2021 High-resolution global map of smallholder and industrial closed-canopy oil palm plantations Earth Syst. Sci. Data 13 1211–31
Erwinda D P H, Muliyani A and Nugroho E S 2021 An estimation method for oil palm replanting potential in Kampar Regency, Province of Riau IOP Conf. Ser.: Earth Environ. Sci. 757 012034
Fritianto A C, Darmawan A, Tokimatsu K and Suwandika M 2018 Estimating the age of oil palm trees using remote sensing technique IOP Conf. Ser.: Earth Environ. Sci. 148 012020
Foley J A et al 2005 Global consequences of land use Science 309 570–8
Gao B 1996 NDWI—a normalized difference water index for remote sensing of vegetation liquid water from space Remote Sens. Environ. 58 257–66
Gaveau D, Locatelli B, Salim M, Husnayaen H, Manurung T, Descals A, Angelsen A, Meijaard E and Schei D 2022 Slowing deforestation in Indonesia follows declining oil palm expansion and lower oil prices PLoS One 17 e0266718
Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D and Moore R 2017 Google Earth engine: planetary-scale geospatial analysis for everyone Remote Sens. Environ. 202 18–27
Hansen M C et al 2013 High-resolution global maps of 21st-Century forest cover change Science 342 850–3
Ismail A and Mamat M N 2002 The optimal age of oil palm replanting Oil Palm Ind. Econ. J. 2 1
Jiang Z, Huete A, Didan K and Miura T 2008 Development of a reflectance vegetation index for remote sensing of vegetation liquid water from space Remote Sens. Environ. 112 3833–45
Lee J S H, Miteva D A, Carlson K M, Heilmayr R and Sif O 2020 Does oil palm certification create trade-offs between environment and development in Indonesia? Environ. Res. Lett. 15 124064
López García M and Caselles V 1991 Mapping burns and natural reforestation using Thematic Mapper data Geocarto Int. 6 31–37
Meijaard E et al 2020 The environmental impacts of palm oil in context Nat. Plants 6 1418–26
Ministry of Agriculture, Indonesia 2017 Tree crop estate statistics of Indonesia 2014–2016 (available at: https://ditjenbun.pertanian.go.id/)
Ministry of Agriculture, Indonesia 2020 The environmental impacts of palm oil in context Nat. Plants 6 1418–26
Ministry of Agriculture, Indonesia 2017 Tree crop estate statistics of Indonesia 2014–2016 (available at: https://ditjenbun.pertanian.go.id/)
Numata I, Roberts D A, Chadwick O A, Schimmel J, Sampaio F R, Leonidas F C and Soares J V 2007 Characterization of pasture biophysical properties and the impact of grazing intensity using remotely sensed data Remote Sens. Environ. 109 314–27
Nurfatriani F and Komarudin H 2019 Optimization of crude palm oil fund to support smallholder oil palm replanting in reducing deforestation in Indonesia Sustainability 11 4914
Nurrochmat D R, Massijaya M Y, Jaya I N S, Ekayani M, Kuncahyo B and Prawira T 2019 Assessing factors to influence the willingness of smallholders to participate in a replanting zonation scheme in Pelalawan District, Riau Province, Indonesia IOP Conf. Ser.: Earth Environ. Sci. 285 012002

Qaim M, Sibhatu K T, Siregar H and Grass I 2020 Environmental, economic, and social consequences of the oil palm boom Annu. Rev. Resour. Econ. 12 321–44

Ramdani F and Hino M 2013 Land use changes and GHG emissions from tropical forest conversion by oil palm plantations in Riau Province, Indonesia PLoS ONE 8 e70323

Rehman S A, Sabiham S, Suidadi U and Anwar S 2015 Historical assessment of forestland conversion to oil palm plantations in Riau and West Kalimantan, Indonesia Int. J. Plant Soil Sci. 6 34–49

Ritung S, Wahyunto N, Sukarman K, Hikmatullah S and Tafakresnanto C 2011 Peta Lahan Gambut Indonesia Skala 1:250.000 (Indonesian peatland map at the scale 1:250,000) (Bogor: Indonesian Center for Agricultural Land Resources Research and Development)

Roy D P, Kovalskyy V, Zhang H, Vermote E F, Yan L, Kumar S and Egorov A 2016 Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity Remote Sens. Environ. 185 57–70

Saoutra W and Saif I 2018 Oil palm moratorium: The future offered The Jakarta Post (available at: www.thejakartapost.com/academia/2018/12/15/oil-palm-moratorium-the-future-offered.html)

Schoneveld G C, Ekowati D, Andrianto A and van der Haar S 2019 Modeling peat- and forestland conversion by oil palm smallholders in Indonesian Borneo Environ. Res. Lett. 14 014006

Souza C M, Roberts D A and Cochrane M A 2005 Combining spectral and spatial information to map canopy damage from selective logging and forest fires Remote Sens. Environ. 98 329–43

Souza C M, Siqueira J V, Sales M H, Fonseca A V, Ribeiro J G, Numata I, Cochrane M A, Barber C P, Roberts D A and Barlow J 2013 Ten-year Landsat classification of deforestation and forest degradation in the Brazilian Amazon Remote Sens. 5 5493–513

Tan K P, Kanniah K D and Cracknell A P 2013 Use of UK-DMC 2 and ALOS PALSAR for studying the age of oil palm trees in southern peninsular Malaysia Int. J. Remote Sens. 34 7424–46

Tucker C J 1979 Red and photographic infrared linear combinations for monitoring vegetation Remote Sens. Environ. 8 127–50

Vijay V, Pimm S J, Jenkins C N and Smith S J 2016 The impacts of oil palm on recent deforestation and biodiversity loss PLoS One 11 e0159668

Wimberly M C, Dwomoh F K, Numata I, Mensah F, Amoako J, Nekochuk D M and McMahon A 2021 Histotical trends of degradation, loss, and recovery in the tropical forest reserves of Ghana Int. J. Digit. Earth 15 30–51

Zhao J, Lee J S H, Elmore A J, Fatimah Y A, Numata I, Zhang X and Cochrane M A 2022 Spatial patterns and drivers of smallholder oil palm expansion within peat swamp forests of Riau, Indonesia Environ. Res. Lett. 17 044015

Zhu Z, Wang S and Woodcock C E 2015 Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsat 4–7, 8, and Sentinel 2 images Remote Sens. Environ. 159 269–77