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Comparison of visual and automated oil palm mapping in Borneo

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Abstract

Around 16 Mha of land is estimated to be under oil palm agriculture in insular Southeast Asia. There is a growing need to verify that palm oil is produced without causing negative environmental effects. Monitoring changes in the extent and condition of oil palm plantations by remote sensing is the first necessary step. The changing appearance of oil palm plantations as they age and the varying types (industrial and small-holder) of oil palm cultivation renders this monitoring task difficult. In this study we assess the potential of visual and automated mapping methods for regional level oil palm monitoring by comparing the results of two recent large scale mapping efforts in Borneo Island, shared by Indonesia and Malaysia. Large differences were found between visual and automated methods, mainly related to the concept of land use vs. land cover. Automated oil palm mapping produced 35% smaller oil palm extent than visual mapping for plantation areas established before 2005, and was not able to detect young or newly established plantations. In total, the visual method detected 8.0 Mha of industrial oil palm plantation area, within which the automated method detected merely 3.8 Mha of closed canopy oil palm, highlighting the crucial importance of visual mapping approaches for outlining boundaries of industrial oil palm plantations. However, the automated approach enabled estimation of the extent of 1) productive closed canopy oil palm area and other land cover types within known industrial plantations and 2) closed canopy oil palm stands outside of known industrial plantations (0.6 Mha). These results advocate the combined use of visual and optical oil palm mapping approaches for comprehensive regional level monitoring of oil palm plantations in insular Southeast Asia.

Keywords: Plantation agriculture; Southeast Asia; Remote sensing; Land use - land cover

1. Introduction

Nearly 90% of the world's palm oil is produced in the humid lowlands (< 300 m above sea level) of Indonesia and Malaysia on the islands of Sumatra and Borneo, and in Peninsular Malaysia (SPOTT 2017). Current oil palm plantation extent in this region (from here on called insular Southeast Asia) is estimated to be over 16 Mha (MOAI 2017; MPOB 2017). The palm oil sector constitutes over 10% of the value of yearly exports and employs up to five million people in the region (SPOTT 2017). At the same time, palm oil production worries observers because the rapid expansion of oil palm plantations has been seen as one of the major causes of forest area loss and other negative environmental effects, destroying wildlife habitat and releasing atmospheric carbon (Fitzherbert et al. 2008; Carlson et al. 2013; Gaveau et al. 2016). Increasingly, consumers want to know that the palm oil they use has not caused negative environmental effects. This requires knowing where oil palm is grown. Improved approaches for monitoring the extent and condition of oil palm plantations are urgently needed to enable comprehensive regional level monitoring of oil palm agriculture in the region.

Mapping of oil palm plantations by remote sensing in insular Southeast Asian conditions is a challenging task. The distribution of oil palm agriculture into both large scale industrial plantations as well as small-holder cultivation places high demands in the spatial resolution of remote sensing data and the mapping methods. A comprehensive oil palm plantation monitoring approach would need to have high enough spatial resolution to capture all different types of oil palm cultivation (e.g. industrial plantations and all the various forms of small-holder farming) and it would need to have high enough temporal frequency (minimum yearly) to provide users with meaningful and up-to-date information, while at the same time

difficult atmospheric conditions severely limit the availability of optical satellite data in the region.

Several studies have used visual interpretation to detect industrial oil palm plantations with 10-30 m resolution optical satellite imagery in insular Southeast Asia (Carlson et al. 2013; Gunarso et al. 2013; Gaveau et al. 2016; Miettinen et al. 2016a; Austin et al. 2017). The large rectangular elements, long linear boundaries, and grid- or contour-planting patterns characteristic of industrial plantations are easily detected by the human eye, and so can be identified by visual interpretation across large areas with medium resolution satellite data (10-30 m) in combination with contextual information (e.g. concession maps) and interpreter knowledge. The reliable identification and delineation of small-holder oil palm plantations by visual interpretation requires very high resolution (< 1 m) imagery, which makes it costly, tedious and slow for regional monitoring activities. This explains why small-holder oil palm plantation maps are not available at regional level.

Fully automated delineation of areas used for oil palm agriculture, on the other hand, is impossible at regional level due to the large variety of land cover types found within areas under oil palm cultivation. Without the contextual information and interpreter knowledge utilized in visual interpretation, newly cleared or young oil palm plantation areas resemble closely bare land, or open areas or shrub-like vegetation. However, when oil palm stands reach closed canopy conditions forming a typical oil palm stand structure with large fronds supported by branchless trunks, they can be separated from other tree cover using radar data (Miettinen and Liew 2011). Subsequently, combination of optical and radar data has been used for oil palm mapping in the region with varying geographical extent and data combinations (Cheng et al. 2016, 2018; Miettinen et al. 2016b, 2017; Torbick et al. 2016).

In this study we compare the results of two recent large scale oil palm mapping efforts in the island of Borneo: 1) a visual industrial oil palm plantation mapping by Gaveau et al. (2016) and 2) an automated oil palm mapping by Miettinen et al. (2017). We analyse the differences between the two approaches, highlighting the strengths and limitations of visual and automated remote sensing based oil palm mapping in insular Southeast Asian conditions. Finally, we summarize the lessons learnt from this study in the context of operational oil palm monitoring in the region and discuss possibilities of combined use of visual and automated oil palm mapping approaches.

2. Materials and methods

2.1. Study area

The study area consists of Borneo Island (~73 Mha) excluding the tiny nation of Brunei in the northern shores of the island. Brunei was left out of the analysis due to the marginal extent of oil palm plantations. The rest of the island is divided into the Malaysian states of Sarawak (~12 Mha) and Sabah (~7 Mha) in the north and the Indonesian Kalimantan (~53 Mha) in the south (Figure 1).

<Insert Figure 1 here.>

The natural ecosystems in Borneo Island consist of various types of evergreen tropical forests ranging from peat swamp forests and mangrove to tropical lowland rainforest and several montane forest types (Corlett 2008). However, over the past 40 years Borneo has experienced rapid conversion of forests into agricultural land, with the percentage of primary forest (including intact and selectively logged forests) in the island dropping from 76% in the 1970s to 51% in 2015 (Gaveau et al. 2014, 2016; see also the Borneo atlas at

www.cifor.org/map/atlas for updates). Simultaneously the area of industrial oil palm plantations has grown rapidly. In Sabah, the fastest oil palm plantation expansion took place already in the 1990s, while in Sarawak and Kalimantan the most rapid expansion has taken place only since 2005 (Figure 2). In Sarawak, industrial oil palm plantation extent doubled from 2005 to 2015, while in Kalimantan the area under industrial oil palm cultivation more than tripled during the same time period.

<Insert Figure 2 here.>

2.2. Oil palm extent datasets

2.2.1. CIFOR visual industrial oil palm plantation mapping

An industrial oil palm plantation map for the year 2015 created by Gaveau et al. (2016) at the Center for International Forestry Research (CIFOR), Bogor, Indonesia, was used in this study (Figure 1). The map was created through visual interpretation of 30 m spatial resolution Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) images. Industrial oil palm plantation areas were identified by distinctive image feature patterns and supporting datasets (e.g. plantation concession data), and validated with very high resolution satellite imagery. The 2015 industrial plantation map also provides information on the approximate year of establishment for each plantation area in seven time steps (1970s, 1990, 1995, 2000, 2005, 2010 and 2015). This information refers to the year when the plantation area was first detected in a series of mapping cycles using historical datasets acquired for the above listed years.

The 2015 map contains 1705 industrial oil palm plantation polygons. The plantation areas were assessed to have 98% user's accuracy and 80% producer's accuracy (see Supplementary Information in Gaveau et al. 2016). For further information on the 2015 industrial oil palm

plantation map please refer to Gaveau et al. (2016). From here on this dataset is referred to as the ‘CIFOR map’.

2.2.2. CRISP automated oil palm mapping

The automated oil palm mapping result used in this study was produced by Miettinen et al. (2017) at the Centre for Remote Imaging, Sensing and Processing (CRISP), Singapore. The mapping was based on a decision tree land cover classification algorithm utilizing a combination of 14 variables derived from medium resolution (10-30 m) optical (Landsat TM and ETM+) and radar imagery (Sentinel-1 and Advanced Land Observing Satellite-2 Phased Array Synthetic Aperture Radar-2), as well as auxiliary datasets (e.g. digital elevation model and water mask). During data pre-processing, all of the datasets were resampled to 30 m spatial resolution, matching also well the spatial resolution of the Landsat datasets used in the production of the CIFOR map introduced above. The classification approach was developed for regional land cover mapping and the process was fully automated with no manual corrections implemented. The data were acquired in 2015, matching the visual oil palm plantation mapping product described above. For full details of the automated land cover classification approach and the regional 30 m resolution land cover map produced, please refer to Miettinen et al. (2017).

The original land cover map (Miettinen et al. 2017) included 11 land cover classes, of which only five classes were found within CIFOR oil palm plantations in significant proportions (Table 1). The ‘Oil palm’ class was extracted from shrub and tree covered areas using a threshold for the difference of HH and HV backscatter in Sentinel-1 data. The algorithm needs a combination of optical data (to identify shrub and tree cover) and radar data (to extract closed canopy oil palm from other shrub and tree cover). It is important to understand

that the 'Oil palm' class includes all closed canopy (but only closed canopy) oil palm stands, regardless of whether they are within or outside industrial plantation areas. Similarly the 'Bare soil' and 'Open' classes in the CRISP map may include lands under development for oil palm plantations or may already be planted with young oil palm trees. A minimum patch size for oil palm detection was set to 11 pixels (~1 ha) in order to reduce speckled errors. The user's and producer's accuracies of the 'Oil palm' class were assessed to be 90% and 71%, respectively (Miettinen et al. 2017). From here on this dataset is referred to as the 'CRISP map'.

<Insert Table 1 here.>

2.3. Analysis approach

The analysis presented here is based on an overlay of the CIFOR and CRISP maps described above. The automatically-produced CRISP map is compared to the visually-produced CIFOR map to evaluate the strengths and limitations of the two mapping approaches. Four main aspects are compared: 1) differences in the detectability of large scale industrial and other types of oil palm plantations, 2) total oil palm extent mapped by the two approaches and their spatial agreement, 3) CRISP map land cover distribution within CIFOR plantations and 4) effect of plantation age on its detectability by the automated mapping method.

3. Results

Visual comparison of very high resolution examples from Google Earth (<https://www.google.com/earth/>) containing different types of oil palm cultivation reveals the most essential differences between the visual and automated oil palm mapping approaches compared in this study (Figure 3). The visual approach detects all areas used for oil palm

agriculture regardless of the phase or condition of the crop but is limited to large scale industrial plantations. The automated mapping only detects existing closed canopy oil palm stands but is not limited to large scale industrial plantations. In the example area covered in Figure 4 one can see that some sections of a large oil palm plantation, which was first detected in 1995, have been recently cleared (most likely for replanting), and are detected as 'Open' and 'Shrub' by the CRISP mapping. Similarly, all newly established plantations would be missed until the first oil palm generation has reached closed canopy conditions (in around 6-8 years of age) and becomes detectable by the automated method analysed in this study. Several patches of 'Tree cover' can also be seen within the plantation area (Figure 4). Although some of these may be detection errors, many were confirmed to be patches of tree cover other than oil palm utilizing very high resolution imagery available in Google Earth. One can also see some areas of oil palm detected outside the large plantation area, too small to be focused on in large scale visual mapping efforts but detectable by the automated method.

<Insert Figures 3 and 4 here.>

Due to their different but complementing strengths, both visual and automated mapping approaches can provide valuable information for oil palm cluster monitoring when used together. However, when applied separately, the two mapping methods analysed in this study deliver highly different impression of the current extent of oil palm agriculture in Borneo. The automated CRISP method detects only 4.4 Mha of oil palm, while the CIFOR oil palm plantation extent is nearly 8.0 Mha (Table 2). Only 3.8 Mha (48%) of the CIFOR industrial plantations are detected as oil palm in the CRISP map. This equals to 87% of all CRISP oil palm area, with the remaining 13% detected outside CIFOR industrial oil palm plantations.

<Insert Table 2 here.>

However, the percentage of areas detected as oil palm in the CRISP map within CIFOR oil palm plantations varies significantly between different parts of Borneo. While in Sabah 63% of the plantation areas are detected as oil palm, in Sarawak and Kalimantan the proportions detected as oil palm are less than 45% (Figure 5). This is believed to be related to the average age of plantations. Sabah has the highest proportion of mature closed canopy plantations with only 11% of plantation established since 2005, while in Sarawak and Kalimantan 53% and 69% of industrial oil palm plantations are less than 10 years old.

<Insert Figure 5 here.>

This theory is further supported by the land cover distribution of the CRISP map inside CIFOR oil palm plantations (Figure 5). Among the areas not classified as oil palm, the classes of 'Bare soil', 'Open' and 'Shrub' combined contain 35% and 44% of CIFOR oil palm plantation areas in Sarawak and Kalimantan, but only 24% in Sabah. These land cover types are to a large extent related to newly established and young oil palm plantations, potentially including a mixture of natural herbaceous or woody ingrowth among oil palm seedlings (Figure 3). In these conditions radar backscatter does not have the typical features of a palm stand (which only become apparent when the canopy closes), making it impossible to detect these areas as oil palm with the methods used to produce the CRISP map. It is important to note however, that bare, open and shrubby areas are often found also within older plantations (e.g. various crop landing sites, roads, failed or damaged section etc.) and do not therefore always constitute an error in automatic detection even within older plantations. They can also indicate clearance and replanting of an old plantation.

Perhaps the most baffling finding in the CRISP automatic mapping results is the relatively high proportion of 'Tree cover' class within the CIFOR oil palm plantations, particularly in Sarawak (Figure 4). The values may be somewhat inflated by inclusion of real patches of other tree cover within the CIFOR industrial plantation polygons (as in Figure 4), but surely also indicate a genuine limitation for automatic detection. Visual examination of some major problem areas with very high resolution data available in Google Earth revealed a significant mixture of other trees among oil palms in the misclassified areas (Figure 3 (f)). This reduces the strength of the typical oil palm radar backscatter signal to such an extent that the area is not classified as oil palm.

The effect of plantation age on the detectability of oil palm by the automated CRISP method is clearly visible in Figure 6. The proportions of areas detected as oil palm within CIFOR industrial plantations older than 10 years (i.e. first detected 2005 or earlier) are 60% for Sarawak, 69% for Sabah and 65% for Kalimantan (calculated from the combined area of plantations older than 10 years). Note that the lower detection rate of plantations older than 25 years (i.e. established before 1995) in Sarawak and Kalimantan decreases the general detection rate of all plantations older than 10 years. Some of these old plantations may already have been cleared for replanting or they may be otherwise in poor conditions with large gaps and natural vegetation ingrowth (see e.g. Figures 3 (f) and 4). The around 40 years old plantations areas (i.e. first detected in the 1970s satellite data), on the other hand, are expected to be already largely in the second rotation of closed canopy oil palm, with potentially some remaining very old unproductive plantation areas. Overall, 65% of CIFOR oil palm plantations older than 10 years were detected as oil palm by the automatic mapping,

52% of the plantations of age 5-10 years (i.e. established between 2005 and 2010) and only 10% of the plantations of age 0-5 years (i.e. established since 2010).

<Insert Figure 6 here.>

4. Discussion and conclusion

In this study we have compared the results of a visual and an automated large scale oil palm mapping approach in insular Southeast Asian conditions. Great differences were found between the two approaches, largely related to the concept of land use vs. land cover. Automated detection methods are limited to interpretation of the physical characteristics of any given area (i.e. land cover), while visual detection methods allow interpretation of land allocation aspects (i.e. land use) using an array of auxiliary information varying from contextual information to interpreter knowledge of the area. Thereby, the greatest strength of visual delineation of oil palm plantation areas is without a doubt the ability to produce boundaries of large oil palm plantations regardless of the development phase of the plantation or the current condition of the crop. This way visual interpretation also allows fast detection and identification of newly cleared oil palm plantation areas. This information is crucial for land use and land use change monitoring purposes (e.g. to evaluate the extent of deforestation caused by oil palm agriculture; Gaveau et al. 2016) and cannot be achieved with fully automated methods on regional level monitoring with currently available materials and methods. Newly cleared oil palm plantation areas with bare soils or herbaceous vegetation do not have any physical land cover characteristics that would make them separable from other bare or herbaceous areas in automated classification.

However, for large scale monitoring purposes visual interpretation is hampered by the amount of work and limited availability of satellite data. Due to the limitations in the level of

detail that can be achieved by visual interpretation in large scale monitoring in practice, visual delineation misses oil palm cultivation activities outside large scale plantations, thereby missing e.g. most of the small-holder oil palm cultivation. Due to the same limitation, it is also not possible to map the actual productive oil palm area or other land cover changes inside industrial plantations. In theory, very high resolution data (< 1 m spatial resolution) would allow highly detailed visual oil palm cultivation mapping, but this is not feasible for regional level oil palm monitoring in insular Southeast Asia due to limited availability of very high resolution satellite data, the prohibitive cost, and the immense amount of manual work needed to fulfil this task.

The automated mapping approach evaluated in this study detected dramatically smaller extent of oil palm, with only 48% of industrial oil palm plantation areas detected in Borneo. Despite this limitation, the dataset is valuable in several ways, and complements the manual detection method. Firstly, the method enables estimation of the extent of mature closed canopy oil palm plantations that produce most of the palm kernels. This may be important information for monitoring the current and modelling the future changes in oil palm production/yields. Secondly, the automated method also provides detailed information on land cover distribution within known large scale industrial plantation areas, which can be used e.g. 1) to analyse the actual production area excluding supporting infrastructure areas (e.g. crop landing sites, roads, offices, mills, staff housing etc.) located within large plantations and 2) to detect failed, damaged or abandoned plantation areas.

But perhaps the most important strength of automated methods is that they are not limited to detection of large scale industrial plantations, but can detect all closed canopy oil palm cultivation activities including large and small plantations (above potential minimum

mapping unit of course). Of all the oil palm detected by the automated method analysed in this study, 13% was detected outside known industrial plantations. These may be small industrially run plantations or small-holder oil palm cultivation. Regardless of the type of these plantations, it would be essential to be able to include these small plantations under operational oil palm monitoring.

But of course the prerequisite of closed canopy applies also in the case of oil palm detection outside large industrial plantations for the automated method analysed in this study. This may be a more restrictive limitation for monitoring small-holder oil palm cultivation compared to industrial oil palm monitoring. The automated method classified parts of known small-holder plantation areas in Borneo as shrub. This may be to some extent due to generally more open structure of small-holder plantations compared to industrial plantations (potentially due to sparser spacing, less fertilizing, poorer condition, more gaps etc.) making the detection of small-holder oil palm cultivation more challenging than the detection of dense industrial plantations, regardless of the size of the plantation area. Unfortunately, the datasets used in this study did not enable analysis of the proportion and types of the oil palm areas detected outside industrial plantations. Nevertheless, we see detection of small-holder oil palm cultivation as one additional potential strength of automated methods, although further methodological development and testing is needed to enhance small-holder oil palm detection and evaluate its efficiency.

Considering the around 20% smaller detection capability of 5-10 years old oil palm plantations (corresponding to around 1 year if plantation establishment is assumed linear) compared to the detection capability of 10-20 year old plantations, and combined with earlier estimation of similar method (Koh et al. 2011), we can roughly estimate that plantations older

than around 6-8 years can be expected to be detected by the automated method analysed in this study. Note that oil palm reaches maturity and starts producing fruits at around 3-4 years of age. This means that although all the oil palm detected by the automated method can be expected to be productive, not all the productive oil palm can be detected. The proportion of this missed section (i.e. around 2-5 years) is likely to vary temporally and spatially within the region, but it only represents around 7-17% of estimated productive life span (up to 30 years) of oil palm trees (MPOC 2017).

Due to the limitations highlighted in this paper, neither visual nor automated mapping alone is sufficient for effective regional level oil palm sector monitoring with currently available materials and methods. Furthermore, due to the variation of the structure of oil palm sector within the region (e.g. proportions of industrial and small-holder activities) and due to the great effect of oil palm age in the detectability by automated methods, it is not possible to use the results derived by one of the approaches to estimate the results for the other approach. The relationship between the results derived by visual and automated approaches will vary greatly both temporally and spatially within the region due to varying history and management practices of oil palm cultivation.

However, we believe that by combining the complementing strengths of visual and automated mapping approaches, it would be possible to build an effective regional oil palm monitoring system with currently available materials and methods. Visual delineation could be used to outline large scale industrial plantations and keep the database updated e.g. on a yearly basis. This information could be supplemented with automated mapping of closed canopy oil palm (both inside and outside known industrial plantations) and other land cover types within known oil palm plantations. This would not only enable improved estimation of

trends in oil palm production levels, but also detailed monitoring of replanting schedules and detection of potential abandoned or damaged areas. Furthermore, after some more methodological development and testing, automated approaches may be able to enable comprehensive monitoring of the extent of small-holder oil palm cultivation, which has become an important topic for the development of sustainable palm oil production.

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References

- Austin, K.G., A. Mosnier, J. Pirker, I. McCallum, S. Fritz and P.S. Kasibhatla. 2017. “Shifting patterns of oil palm driven deforestation in Indonesia and implications for zero-deforestation commitments.” *Land Use Policy* 69: 41-48. doi: 10.1016/j.landusepol.2017.08.036.
- Carlson, K.M., L.M. Curran, G.P. Asner, A. McDonald Pittman, S.N. Trigg and J.M. Adeney. 2013. “Carbon emissions from forest conversion by Kalimantan oil palm plantations.” *Nature Climate Change* 3: 283–287. doi: 10.1038/nclimate1702.
- Cheng, Y., L. Yu, A.P. Cracknell and P. Gong. 2016. “Oil palm mapping using Landsat and PALSAR: a case study in Malaysia.” *International Journal of Remote Sensing* 37: 5431-5442. doi: 10.1080/01431161.2016.1241448.
- Cheng, Y., L. Yu, Y. Xu, H. Lu, A.P. Cracknell, K. Kanniah and P. Gong. 2018. “Mapping oil palm extent in Malaysia using ALOS-2 PALSAR-2 data.” *International Journal of Remote Sensing* 39: 432-452. doi: 10.1080/01431161.2017.1387309.
- Corlett, R.T. 2009. *The ecology of tropical East Asia*. New York: Oxford University Press.
- Fitzherbert, E.B., M.J. Struebig, A. Morel, F. Danielsen, C.A. Brühl, P.F. Donald and B. Phalan. 2008. “How will oil palm expansion affect biodiversity?” *Trends in Ecology and Evolution* 23: 538–45. doi: 10.1016/j.tree.2008.06.012.
- Gaveau, D.L.A., S. Sloan, E. Molidena, H. Yaen, D. Sheil, N.K. Abram, M. Ancrenaz, R. Nasi, M. Quinones, N. Wielaard and E. Meijaard. 2014. “Four Decades of Forest Persistence, Clearance and Logging on Borneo.” *PLoS ONE* 9: e101654. doi: 10.1371/journal.pone.0101654.
- Gaveau, D.L.A., D. Sheil, M.A.S. Husnayaen, S. Arjasakusuma, M. Ancrenaz, P. Pacheco and E. Meijaard. 2016. “Rapid conversions and avoided deforestation: Examining four

decades of industrial plantation expansion in Borneo.” *Scientific Reports* 6: 32017. doi: 10.1038/srep32017.

Gunarso, P., M. Hartoyo, F. Agus and T. Killeen. 2013. “Oil palm and land use change in Indonesia, Malaysia and Papua New Guinea” Geneva: Roundtable of Sustainable Palm Oil. Available at: http://www.tropenbos.org/file.php/1343/4_oil_palm_and_land_use_change_gunarso_et_al.pdf, accessed 23 Feb 2018.

Koh, L.P., J. Miettinen, S.C. Liew and J. Ghazoul. 2011. “Remotely sensed evidence of tropical peatland conversion to oil palm.” *Proceedings of the National Academy of Sciences (PNAS) of the USA* 108: 5127-5132. doi: 10-1073/pnas.1018776108.

Miettinen, J. and S.C. Liew. 2011. “Separability of insular Southeast Asian woody plantation species in the 50 m resolution ALOS PALSAR mosaic product.” *Remote Sensing Letters* 2: 299-307. doi: 10.1080/01431161.2010.520345.

Miettinen, J., C. Shi and S.C. Liew. 2016a. “Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990.” *Global Ecology and Conservation* 6: 67–78. doi: 10.1016/j.gecco.2016.02.004.

Miettinen, J., C. Shi and S.C. Liew. 2016b. “2015 land cover map of Southeast Asia in 250 m spatial resolution.” *Remote Sensing Letters* 7: 701-710. doi: 10.1080/2150704X.2016.1182659.

Miettinen, J., C. Shi and S.C. Liew (2017). “Towards automated 10-30 m resolution land cover mapping in insular South-East Asia.” *Geocarto International* (online first). doi: 10.1080/10106049.2017.1408700.

MOAI. 2017. *Agricultural statistics*. Jakarta: Ministry of Agriculture of Republic of Indonesia. Available at: <http://aplikasi.pertanian.go.id/bdsp/>, accessed 24 Nov 2017.

- MPOB. 2017. *Oil palm planted area by state*. Selangor: Economics and industry development division, Malaysian Palm Oil Board (MPOB). Available at: <http://bepi.mpob.gov.my/index.php/en/>, accessed 24 Nov 2017.
- MPOC. 2017. *The oil palm tree*. Selangor: Malaysian Palm Oil Council (MPOC). Available at: http://www.mpoc.org.my/The_Oil_Palm_Tree.aspx, accessed 24 Nov 2017.
- SPOTT. 2017. *Sustainable Palm Oil Transparency Toolkit (SPOTT)*. London: Zoological Society of London. Available at: <http://www.sustainablepalmoil.org/asia/>, accessed 22 Jun 2017.
- Torbick N, L. Ledoux, W. Salas and M. Zhao. 2016. "Regional mapping of plantation extent using multisensor imagery." *Remote Sensing* 8: 236. doi: 10.3390/rs8030236.

Table 1. Land cover classes of the automatic classification approach. Modified from Miettinen et al. (2017).

Table 2. Oil palm extent statistics for Borneo in 2015 based on the CIFOR and CRISP maps. IOPP refers to industrial oil palm plantations mapped by CIFOR.

Figure 1. Borneo Island with main administrative divisions. Oil palm plantations mapped by Gaveau et al. (2016) shown in dark grey colour.

Figure 2. Expansion of industrial oil palm plantations in Borneo (Gaveau et al. 2016).

Figure 3. Examples of oil palm mapping capability of the CRISP automated method.

Detected: (a) Industrial plantation and (b) dense small-holder plantation. Not detected: (c) sparse small-holder plantation (detected as shrub), (d) newly planted industrial plantation (detected as open), (e) young industrial plantation (detected as shrub) and (f) industrial plantation with significant ingrowth (detected as tree cover). CIFOR visual mapping included all sites except (b) and (c). All examples are around 60x60 m in size.

Figure 4. CIFOR industrial oil palm plantation polygons (in black) overlaid on CRISP land cover map. The adjacent but different plantations polygons indicate areas first detected in different years.

Figure 5. Land cover distribution (CRISP) within industrial oil palm plantations (CIFOR) in 2015.

Figure 6. Proportion of area detected as closed canopy oil palm (CRISP map) within industrial oil palm plantations (CIFOR map), presented by plantation age. 0-5 years refer to plantations first detected in 2015, 5-10 years in 2010 etc. Plantation areas first detected in the 1970s dataset in the CIFOR map were given age of 40 years in the figure.