



AperTO - Archivio Istituzionale Open Access dell'Università di Torino

Detection and characterization of oil palm plantations through MODIS EVI time series

This is the author's manuscript
Original Citation:
Availability:
This version is available http://hdl.handle.net/2318/1696749 since 2020-02-24T19:41:51Z
Published version:
DOI:10.1080/01431161.2019.1584689
Terms of use:
Open Access
Anyone can freely access the full text of works made available as "Open Access". Works made available under a Creative Commons license can be used according to the terms and conditions of said license. Use of all other works requires consent of the right holder (author or publisher) if not exempted from copyright protection by the applicable law.

(Article begins on next page)

Detection and Characterization of Oil Palm Plantations through

2 MODIS EVI Time Series

- 3 Samuele De Petris 1; Piero Boccardo 2; Enrico Borgogno-Mondino 3
- 4 (1,3) DISAFA Department of Agricultural, food and forestry sciences, University of
- 5 Torino, Torino, Italy.
- 6 (2) DIST Interuniversity Department of Regional and Urban Studies and Planning,
- 7 Torino, Italy.
- 8 corresponding author email: <u>samuele.depetris@edu.unito.it</u>
- 9
- 10 Samuele De Petris ORCID: https://orcid.org/0000-0001-8184-9871
- 11 Piero Boccardo ORCID: https://orcid.org/0000-0003-4565-7332
- 12 Enrico Borgogno-Mondino ORCID: https://orcid.org/0000-0003-4570-8013

14 Detection and characterization of oil palm plantations through MODIS

15 **EVI time series**

16 Oil palm is a perennial tree that well fits the humid tropical climate; fresh fruit 17 bunches (FFB) are the palm raw fruit for oil mills. Palm oil is the world highest 18 yielding oil crop determining that palms are extensively planted in South-East 19 Asia, especially in Malaysia, Thailand, and Indonesia where plantations have 20 been spreading in response of the increasing market demand. Cultivation of oil 21 palm in tropical countries is an important economic factor, but, it has already 22 proved of endangering biodiversity and degrading environment with a global 23 impact related to forest loss. Remote sensing well fits requirements of precision 24 farming that many stakeholders involved in palm oil production are currently 25 approaching to decrease or monitor environmental impacts. In this work, an EVI 26 (Enhanced Vegetation Index) time series of 415 images was obtained from the 27 MODIS Vegetation Index 16 days composite product (MOD13Q1-v5) to explore 28 tropical vegetation changes. The EVI time series covers a period of 18 years; it 29 was processed aiming at mapping new oil palm plantations in the reference 30 period, giving an estimate of their age, production and economic value. In this 31 work, a new methodology for oil palm detection and characterization was 32 presented based on local EVI temporal profile analysis. Pixel EVI temporal 33 profile proved to be effective in describing both vegetation macro-phenology and 34 forest loss at that position. Consequently, the proposed algorithm looks for abrupt 35 changes along the local EVI time series (sudden decreasing). The minimum EVI 36 value recorded in the detected changing period is assumed as predictor of the 37 starting date of new plantations, being the latter reasonably related to forest loss 38 and preliminary soil preparation. Starting date is then used by algorithm to 39 estimate oil palm age and, consequently, the present local (potential) production.

40	Accuracy assessment showed an overall accuracy in new palm oil plantations
41	detection of about 94%. Starting age estimation proved to be accurate enough:
42	76% of estimates, in fact, were placed in a range of uncertainty of 1 year.
43	Keywords: Oil Palm MODIS FVI Time Series Analysis Plantation Age Palm
13	neduction EED Dalm Detection Domes
44	production, FFB, Pann Detection, Borneo.

45

46 1. Introduction

47 Palm oil is the world highest yielding oil crop. The consumption of palm oil over the 48 world is growing through the years: 55 Million tons in 2012-2013, over 60 Million tons 49 in 2015-2016 (Chong 2017). According to FAO (FAO 2018), presently, the two largest 50 palm oil producing countries are Indonesia and Malaysia. Elaeis guineensis Jacq. is a 51 palm species of the Arecaceae's family commonly called Oil palm; it is planted 52 extensively in South-East Asia, especially in Malaysia, Thailand, and Indonesia. In 53 Indonesia plantations showed an increasing linear trend that brought the 4 million 54 hectares in 2000 up to 11 million hectares in 2015 (Chong 2017). Oil palm is a 55 perennial tree that well fits the humid tropical climate (high precipitation rate, high solar 56 radiation and warm temperature between 24–32 °C (Corley and Tinker 2008). Oil palm 57 plantations, generally, have a triangular pattern (9 m row spacing), to optimize sunlight 58 penetration (Basiron 2007). The majority of planted oil palms are a small mixture of 59 hybrid clones, i.e. Dura x Pisifera, (Chong 2017), resulting in a uniform pattern at the 60 ground; this makes oil palms different from other trees or forest in satellite imagery 61 (Shafri et al. 2011). Cultivation of oil palm in tropical countries is an important 62 economic factor, but, it greatly endangers biodiversity and degrades the environment 63 with a global impact (Koh and Wilcove 2008). In these regions, in fact, the last world

tropical forests are present (Iremonger et al. 1997), containing numerous endemic or 64 65 rare species, many of which are restricted to forest habitats (Mittermeier et al. 2004; Sodhi et al. 2004; Koh 2007). Over-logged forests are often considered as degraded 66 67 habitats by governments, just waiting for conversion to agriculture. This fact, has encouraged the transformation of secondary (logged) forests to oil palm plantations in 68 69 Malaysia and Indonesia (McMorrow and Talip 2001). From this point of view remote 70 sensing can support a more efficient plantation strategy that takes into account 71 environmental/ecological instances. Moreover, plantations monitoring by remote 72 sensing well fits requirements of precision farming that many stakeholders are currently 73 approaching to decrease environmental impacts of their practices. Private owners and 74 local farmers are, in fact, interested in assessing crop conditions along its growing 75 season; differently, governmental institutions and environmental associations long for 76 the possibility of continuously monitoring the state of the national natural/crop capital. 77 Among the available remotely sensed data, the NASA's sensors MODerate resolution 78 Imaging Spectroradiometer (MODIS) onboard the Terra and Aqua satellites have been 79 widely used in a variety of studies (Testa et al. 2018; Colombo et al. 2011; Hmimina et 80 al. 2013; Soudani et al. 2008; Zhang et al. 2003). Thanks to the two twin MODIS 81 instruments, MODIS data are acquired globally averagely twice per day per instrument 82 at the spatial resolutions of 250 m, 500 m and 1 km at nadir, depending on the 83 considered spectral band. MODIS imagery is distributed at various pre-processing 84 levels and, with respect to the temporal resolution, data are released as both daily and 85 composites products, the latter generated at different compositing steps (8-day, 16-day, 86 monthly). Composite data have some advantages in respect of daily data, since the 87 compositing process strongly reduces cloud, snow and sensor noise effects (Solano et al. 88 2010). In this work a time series of EVI (Enhanced Vegetation Index, Huete et al. 1999)

89 maps, covering the period 2000-2018, was generated from the MODIS Vegetation 90 Index products (MOD13Q1-v5) with the aim of automatically detecting new oil palm 91 plantations and possibly giving an estimate of their age, production and economic value. 92 EVI spectral index has proved to be more effective in mapping vegetation in those 93 situations where atmospheric scattering and vegetation vigor are high, and background 94 contribution to signal is not negligible (Hufkens et al. 2012; Xiao et al. 2003). These are 95 exactly the conditions that can be found in the Borneo area, therefore suggesting the 96 adoption of EVI in place of the ordinary NDVI (Normalized Difference Vegetation 97 Index). It is worth to remind at this point, in this work authors, while mapping oil palm 98 plantations, voluntarily did not refer to any of locally available data to test accuracy of 99 deductions. One of requirements of this work was, in fact, to "objectively" map 100 plantations in spite of any official existing data. This was mandatory since the method 101 was intended to define a procedure to control the reliability of farmers/company 102 communications about the size and position of their plantations to National Institutions. 103 Consequently, only external data and self-conducted photointerpretations from available 104 high resolution satellite images were taken into account to test accuracy of deductions.

105

Materials and Methods

106 **2.1** Study Area

2.

107 The study area is located in the South of Kalimantan Tengah (Central Kalimantan), a 108 province of Indonesia belonging to the Borneo island (2°53'57.58"S - 112°22'6.47"E , 109 WGS-84 reference frame). It was selected as representative of a wider area having 110 similar features, based on landscape markers criteria (rivers, coast, etc.), resulting in 111 about 2.95 million hectares (Fig. 1). According to Köppen classification, local climate is 112 considered tropical rainforest. It is dominated by low-pressure system all over the year generating no thermal and moisture seasonality. According to USDA (United States Department of Agriculture) Soil Taxonomy, local soil is mainly labelled as *Oxisol* with a high aluminium and low phosphate content that could hinder plant growth. Morphology is generally flat without significant reliefs, even if some local microsites conditions could affect vegetative vigour of plantation. Nevertheless, edaphic conditions of area can be retained constant at the small scale.

119 [Figure 1]

120 2.2 Available Data

An EVI (Enhanced Vegetation Index) image time series (hereinafter called ETS), composed of 415 images covering the period 18/02/2000 - 18/02/2018, was generated from the MOD13Q1-v5 dataset available from the NASA LPDAAC collection (Solano et al. 2010). According to Huete (1999) EVI is a vegetation index designed to enhance vegetation signal in high biomass regions (like equatorial rainforest) improving monitoring through a de-coupling of the background signal and a reduction of the atmosphere influence. EVI is computed according to Equation (1):

128
$$EVI = \frac{G (\rho NIR - \rho RED)}{(\rho NIR + C1 \rho RED - C2 \rho BLUE + L)}$$
(1)

129 where ρ are at-the-ground reflectances, L is the canopy background adjustment that 130 addresses nonlinear, differential NIR and red radiant transfer through a canopy, and C1, 131 C2 are the coefficients of the aerosol resistance term, which uses the blue band to 132 correct aerosol influences in the red band. The coefficients adopted in the EVI 133 algorithm are, L = 1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5. As reference data to validate results from ETS processing, the Global Forest Change (GFC) 2000-2016 134 135 dataset-v1.4 (Hansen et al. 2013) obtained from the was

136 Hansen/UMD/Google/USGS/NASA system in raster format. GFC is divided into 10 x 137 10 degree tiles, consisting of seven files per tile. All files are unsigned 8-bit having a 138 spatial resolution of 1 arc-second per pixel (approximately 30 meters per pixel at the 139 equator). Year of gross forest cover loss event grid (lossyear, hereinafter called GFC-140 YL) is defined as a disaggregation of total forest loss to annual time scales. In this 141 dataset, zero values mean "no forest loss", values in the range 1-16 (2000-2016) 142 indicate the year when a forest loss detection occurred. For this work, starting from 143 native GFC-YL, a new forest cover loss 2000-2016 (hereinafter called GFC-L) layer 144 was generated representing forest losses in the period 2000-2016, defined as both stand-145 replacement disturbance, or changes from a forest to non-forest state. In GFC-L pixels 146 where forest loss was detected are coded as 1, while the others were set to 0. Both the 147 GCF raster layers were preventively projected into the WGS84 UTM 49 S reference 148 system, setting a Ground Sampling Distance (GSD) of 250 m. Image processing for oil 149 palm plantations detection was achieved by a self-developed routine implemented in 150 IDL 8.0 programming language. Results and intermediate steps were managed by free 151 GIS software (QGIS 2.18.4 and Saga GIS 6.2).

152

2.3 Mapping new oil palm plantations

153 A new methodology for oil palm detection and characterization was developed and 154 implemented based on temporal profile analysis of each ETS pixel. EVI temporal 155 profile proved to be effective in describing dynamics of vegetation cover with particular 156 concern on its macro-phenology. The detection algorithm analyzes local ETS profile 157 looking for an abrupt change in EVI values (sudden decreasing) along the considered 158 period (18 years). Candidate pixels, possibly representing new oil palm plantations, were detected with reference to the 1st order polynomial (eq. 2) approximating EVI 159 160 local time profile in the whole reference period; the estimated gain value of the 161 computed regression line was assumed as predictor of new oil palm plantations and 162 saved in a new image layer, hereinafter called G(x,y).

163

164
$$EVI(DOY) = G(x, y) \cdot DOY + O(x, y)$$
(2)

165

where DOY is the generic Day of the Year, G(x,y) and O(x,y) the estimated gain and offset values at that position in the image (ETS).

Theoretical assumption was that, in tropical areas, new oil palm plantations show a gain higher than natural vegetation, being the EVI values of the new cover significantly higher than the one ordinarily expressed by natural vegetation. The ideal EVI temporal profile of pixels interested by new plantations shows three periods of interest (Fig. 2).

172 [Figure 2]

173 In the first period (A), previously existing forest cover (natural or semi-natural 174 vegetation like forest or secondary logged forest) is still present. In phase B, a sudden 175 EVI decreasing indicates that a land cover change is taking place, probably related to 176 the combined effect of pre-existing vegetation cut and consequent soil preparation 177 activities, preceding palm seedlings planting. The point when the minimum value of the 178 local ETS profile could be found, was assumed as the new plantation starting moment 179 (see forward on and Fig. 2). The C phase is the one when new planted palms begin to 180 improve their biomass and grow, determining a progressive increase of EVI values. The 181 final (mature) stage of palm growing corresponds to a new higher plateau in ETS. This 182 determines that, in this condition, the overall regression line shows higher and positive 183 gain values than those that a persisting forest cover would have showed. In general, can 184 be observed that when natural vegetation is constantly present, yearly EVI trend is 185 slightly varying with no remarkable profile steep trait, determining gain values of

186 regression line close to zero. Differently, if a new plantation occurs, EVI temporal 187 profiles suddenly decreases at the moment of forest cut, but, after a transitional period, 188 it reaches a new state of vigor corresponding to higher EVI values. The above 189 mentioned succession well fits the ordinary practice for oil palm plantations, that mainly 190 follows 3 steps (Carlson 2012): I) Forest or previous vegetation cutting; II) area burning 191 (fires are considered to be a cheap and effective method to clear and maintain land for 192 agricultural and plantation development (Marlier 2015); III) soil preparation and new 193 seedlings planting. The abrupt EVI value decreasing that occurs when natural 194 vegetation is cut, the consequent oil palm planting and growing determines a significant 195 increasing of line gain, in general higher than 2.0. This reference value was found 196 exploring the behaviour of 200 control points (CPs) testing in the area locations with 197 and without oil palms. CPs were obtained by photointerpretation of 2 available Sentinel-198 2 RGB true color composites (R: band 4, G: band 3; B: band 2) from the T49MFS and T49MFT tiles, respectively acquired on 2018/02/08 and 2018/02/13; 100 CPs were 199 200 placed in evident OP areas and 100 in NOP ones (Fig. 3). The local value of G(x,y) was 201 therefore extracted for each CP, determining two groups (OP and NOP) of G values. To 202 test their a-priori separability a Jeffries-Matusita test (Richards and Richards, 1999) was 203 achieved. To select a proper threshold for G, the mean (μ) and the standard deviation 204 (σ) values of G were computed for NOP points.

205 [Figure 3]

To map ETS pixels that potentially suffered from changes from natural vegetation to oil palm in the reference period, G(x,y) was thresholded to separate potential oil palm (OP, $G(x,y) \ge 2.0$) pixels from the others (NOP, G(x,y) < 2.0), obtaining a rough map of potential new oil palm plantations (Fig. 6a and 6b) with the following codes: 1= Oil Palm (OP), 0 = Not-OP (NOP). Raster classification was vectorised and refined deleting (by ordinary GIS vector map editing tools) all those polygons smaller than 100 ha,
being declared plantation average size in general higher of this value, typically
following a rectangular pattern of 1000 m x 300 m (Fig. 4).

- 214 [Figure 4 in the text, on the left]
- 215

2.4 Estimating Starting Date and Age of Plantations

216 The age of oil palm plantation is an important parameter for crop management: it is a 217 good predictor of yearly yield and conditions the quality and quantity of the *fresh fruit* 218 bunches (FFB). According to the above mentioned classification, ETS profile of all the 219 OP pixel were analyzed at year level looking for the moment of the vegetation loss 220 preceding oil palms plantation. The minimum EVI value along the local ETS was 221 assumed as predictor for new plantations starting date. Unfortunately, many outliers 222 along ETS made not possible to operate on the raw ETS, making desirable a preliminary 223 ETS filtering aimed at minimizing effects of local EVI anomalous variations (Fig. 7). 224 Filtering was achieved by a "customized" low pass filter having a kernel size of 15 225 observations (7 preceding and 7 following the central one) running along ETS. The size 226 of the kernel was set according to the expected detectable phenology of oil palm from 227 ETS as reported in Lam Kuok Choy (2016), where about 6-7 months seem to represent 228 the lasting of the "low vigour" phase of oil palm phenology. In this period sudden EVI 229 variations could be reasonably related to anomalous values to be smoothed.

Filter was applied selectively according to the difference between the EVI center value of the sliding window and its estimate from the local regression line. If difference was larger than 0.15 points of EVI filter was applied, otherwise it was not. The threshold of 0.15 was selected in respect of repeated visual interpretation of reference EVI profiles randomly sampled from the image. Selective smoothing permitted to cut off short-term ETS fluctuations, enhancing long-term ones. With respect to the filtered ETS, for each 236 OP pixel, the minimum EVI value was found and the correspondent year number saved 237 in a new image layer (Fig. 8b). A new raster map was therefore generated representing, 238 in the space domain, the time distribution of new plantations. The age of plantations 239 was consequently computed at each position by differencing the estimated planting year 240 with present (2018, Fig. 8a). This method proved to be able to detect the moment when 241 extensively soil practices occurred (period III) making possible to overcome the 242 uncertainty related to land cover changes possibly due to other reasons (agroforestry, 243 forest logging, natural disturbances, etc.). In fact, many methods based on remotely 244 sensed data are able to detect stand replacing disturbances resulting by land cover 245 change (e.g. forest logging, period I) without making distinctions or explicit which step 246 of land cover transition they detect. Analyzing some representative oil palm ETS pixel 247 we found that the land cover transition, in general, proceeds on for more than one year 248 before reaching the EVI minimum value determining a time lag between forest cut and 249 plantation of new oil palm seedlings. For this reason, authors took into account only the 250 period III as plantation starting moment and consequently it was used to calculate the 251 strongly related age of plantation.

252

2.5 Estimating oil palm production

253 Oil palms produce FFB that represent the raw material for palm oil mills. Oil is 254 extracted from the pulp of the fruit or from the kernel. Production can be affected by 255 various internal and external factors. Internal factors include age and oil palm 256 breeds/variety; external factors include rainfall, drought, disease, soil fertility and 257 moisture, harvesting efficiency (Chong 2017). Thus, to give an estimate of production, 258 all the above mentioned factors would have to be taken into consideration. 259 Nevertheless, a good synthetic predictor of yield is the age of plantation itself. The 260 relationship of yield of oil palm and age establishes a sigmoid shape, fitting a nonlinear

261 regression growth model across its life cycle (Khamiz et al. 2005). Thus, by retrieving 262 the age information of oil palms and the total planted area using remote sensing, the 263 total FFB production of the mentioned area can be roughly estimated using a regression 264 model (Khamiz et al. 2005). Ismail and his collaborators (2002) proposed a time 265 dependent unitary production (UP) curve for oil palm (Fig. 5), relating FFB yearly yield (tons FFB ha⁻¹ yr⁻¹) with the age of plantation (annual basis). Consequently, authors 266 267 used it as a look up table relating the estimated age of plantation to the expected UP in 268 2018. To give an estimation of local production (LP) UP was multiplied by the area of 269 each MOD13Q1 pixel. A map of expected LP was, therefore, generated for the year 2018 (Fig. 10a). 270

271 [Figure 5]

272

2.6 Economic value of oil palm plantations

273 According to FAO dataset (FAO 2018), Indonesia FFB annual producer price (US Dollar tonFFB⁻¹), in refers to 2016, is 111 US Dollar tonFFB⁻¹. Later reference time 274 275 (2017-2018) there are not available, nevertheless, actually FAO data is the most reliable 276 data about FFB price. Therefore, a new estimate production map was generated. 277 Multiplication between FFB annual producer price and LP until 2018 a new plantation 278 economic value map (Fig. 10b) was generated and summarized in table 1. Total 279 economic value of whole study area, in refers to 2018 yield and using 2016 FAO 280 producer price, is about 1.2 Billions USD.

281 **3. Results and Discussion**

282 In respect of the above mentioned procedure, oil palm plantations mapping was

achieved computing the 1st order polynomial approximating EVI local time profile in

the whole reference period and mapping the correspondent gain value, G(x,y). OP were

285 detected by thresholding G(x,y). According to the previously mentioned statistical 286 analysis, the selected threshold to separate OP from NOP pixels was set to 2.0. 287 The Jeffries-Matusita (JM) test was successful, indicating that OP and NOP control 288 points were statistically separable. The JM score was, in fact, 1.93. Concerning G(x,y)289 threshold selection, the mean (μ) and standard deviation (σ) values of G were computed 290 for NOP points. NOP μ and σ resulted respectively 0.109 and 0.913. Considering a 291 confidence interval of 95 % , corresponding to $\mu + 2\sigma = 1.935$, we admitted that OP 292 pixels could be identified looking for local G values higher than this number. 293 Consequently, a threshold value of 2.0 was selected for G(x,y) to separate OP from 294 NOP pixels. OP detection results are shown in maps of figure 6.

295 [Figure 6]

296 Classification accuracy assessment was achieved with reference to GFC-L. Refined 297 vector map was converted back to the raster format by nearest neighbour resampling, 298 making it consistent with GCF-L (GSD = 250 m). It is worth to remind that GFC-L 299 represents the forest loss occurred in the period 2000-2016, that authors assumed to be 300 potentially and totally due to new oil palm plantations in the same period. In fact, in this 301 region new palm plantations are the first reason of forest loss (Curran 2004), making 302 this assumption reasonable. Concerning new oil palm plantation detection the proposed 303 method, based on the thresholding of the gain value of the regression line computed 304 along the whole ETS, proved to be effective: overall accuracy was found to be equal to 305 94%. In the area about 545394 ha (18.5% of the whole study area) were converted from 306 forest to oil palm plantations in the reference period (2000-2018). Gain value of the line 307 interpolating the entire ETS at pixel level proved to be a good discriminant to map 308 vegetation changes and, in particular, those where the following succession occurred: 309 forest vegetation-cutting-oil palm plantation. In fact, replacement of forest with other

surface types (e.g. urban or bare soil) would have determined lower, possibly negative,
values of gain and not highly positive as the threshold value proposed in this work.
Concerning plantations age estimates the maps of figure 8 were produced according to
the proposed method, after selective filtering of the local EVI temporal profiles of OP
pixels (an example of EVI profile for a generic OP pixel is reported in figure 7).

315 [Figure 7]

316 [Figure 8]

317 Estimation of plantations age proved to be more critical; transition matrix was 318 calculated by difference between map of plantations age estimates and GCF-YL. 319 Correspondent cumulative frequency distribution of absolute differences is reported in 320 figure 9. It shows that only 47% of detected plantations present differences equal to 0, 321 i.e. correctly dated. Nevertheless, it must be considered that the proposed method gives 322 an estimate of the moment when soil preparation/new seedlings occurred. Differently, 323 the reference dataset (GCF-LY), maps the moment of forest loss determining a time lag 324 between the two estimates. Considering that a time delay of one year between previous 325 vegetation cutting and planting of new oil palm seedlings is reasonable, all differences 326 included in the range ± 1 year have to be considered not significant. According to this 327 approach it can be noted from figure 9 that 76% of the observations is included in this 328 range, making age of plantations estimates satisfactorily accurate.

329 [Figure 9]

330 Size and economic value of present plantations that were started in the reference period331 were consequently estimated from the local estimate of the age of plantations as mapped

at the previous step. Results are reported in figure 10a and 10b and table 1.

333 [Figure 10]

It is worth to remind that, results about potential production and economic value must be considered purely indicative. In fact, they can be highly moved from the expected value if unknown plant diseases or unfavorable microsite conditions are present in the area.

338 [Table 1]

339 3. Conclusions

340 MODIS derived EVI time series proved to be effective to map and characterize new oil 341 palm plantations. Detection of new plantations based on local temporal profile analysis 342 revealed to be accurate enough (overall accuracy = 94 %), suggesting that time 343 discriminant is basic in assessing vegetation cover. It also proved to make possible give 344 an approximate estimation of the starting date of new plantations and, consequently, of 345 new productions in the area if a unitary production curve is available. The methodology 346 proposed is useful to different oil palm stakeholder, i.e. local owners and farmers could 347 help to optimize yield, reducing environmental impact and making timely practices in 348 the areas most needy in a precision agriculture contest. Also government authorities or 349 environmental monitoring organizations could use this methodology to detect and 350 assessing agricultural/natural capital and monitoring related environmental and socio-351 economic impacts. Many limitations, at the moment, still persist: a) detected changes in 352 vegetation cover can be also related to abiotic or biotic disturbance like wildfire, plant 353 diseases, human clear cut. Auxiliary data from other map or institutional source could 354 help to make result more reliable from this point of view; b) production estimates are 355 based on a literature-derived curve of UP. It is not clear if this curve must be better 356 calibrated according to ground data specifically referring to the explored area; c) 357 production estimates are strictly related to the estimate of the date of beginning of plantations. At the moment, the approximation in this estimate in our study area shows 76% of accuracy using Hansen (2013) dataset as reference map. Actually it doesn't know if the persisting error is due to time lag induces by reference method adopted or to our proposed method. Nevertheless, GFC dataset it is currently the only available and reliable one for tropical vegetation change detection d) future experiences trying to apply the same methodology are expected to be based on MOD13Q1 version 6 datasets, since the version 5 is going to be dismissed from LPDAAC.

365

366	Acknowledgements

- 367 We thank Dr. Costantin Sandu for assistance with forest change map. We thank our colleagues
- 368 dr.Andrea Lessio and dr. Gianmarco Corvino who provided insight and expertise that greatly
- assisted the research.

370 Disclosure statement: No potential conflict of interest was reported by the authors.

371 **References**

- 372 Ismail, A., and Mamat, M. N. 2002. "The Optimal Age of Oil Palm Replanting". Oil
- 373 palm industry economic journal 2(1)/2002.
- Basiron, Yusof. 2007. "Palm oil production through sustainable plantations." European

Journal of Lipid Science and Technology, 109(4), 289-295.

376 https:/risc/doi.org/10.1002/ejlt.200600223

- 377 Carlson, K. M., Curran, L. M., Ratnasari, D., Pittman, A. M., Soares-Filho, B. S.,
- 378 Asner, G. P., ... & Rodrigues, H. O. 2012. "Committed carbon emissions,
- deforestation, and community land conversion from oil palm plantation
- 380 expansion in West Kalimantan, Indonesia." Proceedings of the National
- 381 Academy of Sciences, 109(19), 7559-7564.
- 382 https://doi.org/10.1073/pnas.1200452109

Chong, K. L., Kanniah, K. D., Pohl, C., and Tan, K. P.2017 "A review of remote 383 384 sensing applications for oil palm studies." Geo-spatial Information Science, 385 20(2), 184-200. https://doi.org/10.1080/10095020.2017.1337317 386 Colombo, R., Busetto, L., Fava, F., Di Mauro, B., Migliavacca, M., Cremonese, E., 387 Galvagno, M., Rossini, M., Meroni, M., Cogliati, S., Panigada, C., Siniscalco, 388 C., di Cella, U.M. 2011. "Phenological monitoring of grassland and larch in the Alps from Terra and Aqua MODIS images". Italian Journal of Remote Sensing-389 390 Rivista Italiana Di Telerilevamento 43, 83-96. 391 https://doi.org/10.5721/itjrs20114336 392 Corley, R. H. V., & Tinker, P. B. 2008. The oil palm. John Wiley & Sons. 393 Curran, L. M., Trigg, S. N., McDonald, A. K., Astiani, D., Hardiono, Y. M., Siregar, P., 394 Caniago I., Kasischke E. 2004. "Lowland Forest Loss in Protected Areas of 395 Indonesian Borneo". Science, 303(5660), 1000-1003. 396 https://doi.org/10.1126/science.1091714 397 FAO - Food and Agriculture Organization of the United Nations. 2018. "FAOSTAT". 398 Accessed June 18, 2018 from http://www.fao.org/faostat/en/#home 399 Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, 400 D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. 401 Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. "High-402 Resolution Global Maps of 21st-Century Forest Cover Change". science, 403 342(6160), 850-853. https://doi.org/10.1126/science.1244693 404 Hmimina, G., Dufrêne, E., Pontailler, J. Y., Delpierre, N., Aubinet, M., Caquet, B., 405 Gross, P. 2013. "Evaluation of the potential of MODIS satellite data to predict 406 vegetation phenology in different biomes: An investigation using ground-based

407	NDVI measurements". Remote Sensing of Environment, 132, 145-158.
408	https://doi.org/10.1016/j.rse.2013.01.010
409	Huete, A., Justice, C., and Van Leeuwen, W. 1999. "MODIS vegetation index
410	(MOD13)". Algorithm theoretical basis document, 3, 213.
411	https://doi.org/10.1016/s0034-4257(99)00022-x
412	Hufkens, K., Friedl, M., Sonnentag, O., Braswell, B. H., Milliman, T., & Richardson,
413	A. D. 2012. "Linking near-surface and satellite remote sensing measurements of
414	deciduous broadleaf forest phenology". Remote Sensing of Environment, 117,
415	307-321. https://doi.org/10.1016/j.rse.2011.10.006
416	Iremonger, S., C. Ravilious, and T. Quiton. 1997. "A Global Overview of Forest
417	Conservation". Center for International Forestry Research and World
418	Conservation Monitoring Centre. Cambridge, U.K. CD-ROM.
419	Khamis, A., Ismail, Z., Haron, K., Tarmizi, A. 2005. "Nonlinear Growth Models for
420	Modeling Oil Palm Yield Growth". Journal of mathematics and statistics, 1(3),
421	225-233. https://doi.org/10.3844/jmssp.2005.225.232
422	Koh, L. P. 2007. "Potential habitat and biodiversity losses from intensified production
423	of different biodiesel feedstocks". Conservation Biology 21:1373-1375.
424	https://doi.org/10.1111/j.1523-1739.2007.00771.x
425	Koh, L. P., and D. S. Wilcove. 2008. "Is Oil Palm Agriculture Really Destroying
426	Tropical Biodiversity?". Conservation Letters 1 (2): 60-64. doi:10.1111/j.1755-
427	263X.2008.00011.x.
428	Lam Kuok Choy.2016." The analysis of rainfall variability and response of oil
429	palm phenology in tropical climate using MODIS vegetation index".
430	Proceedings of Geospatial World Forum 2016, The Netherlands.

431	Marlier, M. E., DeFries, R. S., Kim, P. S., Koplitz, S. N., Jacob, D. J., Mickley, L. J., &
432	Myers, S. S. 2015. "Fire emissions and regional air quality impacts from fires in
433	oil palm, timber, and logging concessions in Indonesia". Environmental
434	Research Letters, 10(8), 085005. https://doi.org/10.1088/1748-
435	9326/10/8/085005
436	McMorrow J., and Talip M. A. 2001. "Decline of forest area in Sabah, Malaysia:
437	Relationship to state policies, land code and land capability". Global
438	Environmental Change, 11(3), 217-230. https://doi.org/10.1016/s0959-
439	3780(00)00059-5
440	Mittermeier, R. A. A., Gil, P. R., & Hoffman, M. 2004. "Hotspots Revisited: Earth's
441	biologically richest and most endangered ecoregions". CEMEX/Agrupacion
442	Sierra Madre. Sierra Madre. https://doi.org/10.5860/choice.38-0922
443	Muratni, R., Hanafi, I., & Kurnaen, A. (2016). Analysis of Conversion of Forest Land to
444	be Oil Palm Plantation Area in the District of North Barito Central Kalimantan
445	Province. International Journal of Ecosystem, 6(1), 14-24.
446	Shafri, H. Z., Anuar, M. I., Seman, I. A., & Noor, N. M. 2011. "Spectral discrimination
447	of healthy and Ganoderma-infected oil palms from hyperspectral data".
448	International journal of remote sensing, 32(22), 7111-7129.
449	https://doi.org/10.1080/01431161.2010.519003
450	Sodhi, N. S., Koh, L. P., Brook, B. W., & Ng, P. K. 2004. "Southeast Asian
451	biodiversity: an impending disaster". Trends in ecology & evolution, 19(12),
452	654-660. https://doi.org/10.1016/j.tree.2004.09.006
453	Solano, R., Didan, K., Jacobson, A., & Huete, A. 2010. "MODIS vegetation index
454	user's guide (MOD13 series)". Vegetation Index and Phenology Lab, The
455	University of Arizona, 1-38.

456	Soudani, K., Le Maire, G., Dufrêne, E., François, C., Delpierre, N., Ulrich, E., &
457	Cecchini, S. 2008. "Evaluation of the onset of green-up in temperate deciduous
458	broadleaf forests derived from moderate resolution imaging spectroradiometer
459	(MODIS) data". Remote Sensing of Environment, 112(5), 2643-2655.
460	https://doi.org/10.1016/j.rse.2007.12.004
461	Testa, S., Soudani, K., Boschetti, L., Borgogno-Mondino, E. 2018. "MODIS-derived
462	EVI, NDVI and WDRVI time series to estimate phenological metrics in French
463	deciduous forests". International Journal of Applied Earth Observation and
464	Geoinformation, 64, 132-144. https://doi.org/10.1016/j.jag.2017.08.006
465	Xiao, X., Braswell, B., Zhang, Q., Boles, S., Frolking, S., & Moore III, B. 2003.
466	"Sensitivity of vegetation indices to atmospheric aerosols: continental-scale
467	observations in Northern Asia". Remote Sensing of Environment, 84(3), 385-
468	392. https://doi.org/10.1016/s0034-4257(02)00129-3
469	Zhang, X., Friedl, M. A., Schaaf, C. B., Strahler, A. H., Hodges, J. C., Gao, F., and
470	Huete, A. 2003. "Monitoring vegetation phenology using MODIS". Remote
471	sensing of environment, 84(3), 471-475. https://doi.org/10.1016/s0034-
472	<u>4257(02)00135-9</u>
473	
474	
475	
476	
477	MAIN TEXT WORD COUNT: 3741 words; 18 570 characters (spaces excused).
478	
479	
480	

Table 1. Column 1: Estimated age of mapped new plantations. Column 2: Area
percentage of new plantations at the ith year in respect of the total. Column 3: Estimated
production (Ton FFB yr-1) of the new plantations detected at the ith year. Column 4:
Estimated income from the new plantations detected at the ith year.

Class Age	Area % (Tot OP)	Ton FFB yr ⁻¹ for Class Age	Producer Price (M USD tonFFB ⁻¹)
18	6.03%	0.63	69.64
17	3.84%	0.40	44.94
16	6.79%	0.72	80.44
15	8.13%	0.87	96.38
14	10.75%	1.15	127.43
13	10.71%	1.16	129.25
12	17.30%	1.90	210.39
11	21.76%	2.38	264.62
10	8.83%	0.98	108.68
9	3.30%	0.37	40.70
8	1.46%	0.16	17.47
7	0.66%	0.07	7.57
6	0.26%	0.02	2.63
5	0.02%	0.0014	0.16
4	0.01%	0.0003	0.03
3	0.13%	0.0031	0.34
2	0.02%	-	-
1	0.005%	-	-
New Plantations	0.01%	-	-
TOT OP	545394 ha	10.82	1200.66



495 Figure 1 MANCA LA LEGENDA







504 Figure 3



509 Figure 4



511 Figure 5



- 515 Figure 6



521 Figure 7







- 527 Figure 8





545 Figure 9



- 561 Figure 10

578	Figure 1. The study area is located in the South of Kalimantan Tengah (Central
579	Kalimantan), a province of Indonesia (Borneo island) (WGS84 reference frame).
580	Figure 2. Oil palm ETS where the main management phases are indicated: A)
581	previously existing forest cover; B) forest loss; C) palm growing phase. Red circle show
582	the estimated plantation starting date. Dotted line is the 1 st order polynomial
583	interpolating the yearly EVI profile of a generic OP pixel, $EVI=G(x,y)\cdot DOY+O(x,y)$.
584	G(x,y) is the local Gain value and $O(x,y)$ the local offset value.
585	
586	Figure 3. A) Map showing the CPs position in the study area (WGS84 Reference
587	Frame). B) Box plot of CPs gain value for OP and NOP pixels.
588	
589	Figure 4. Sentinel-2 RGB true colour composite (tile T49MFS, date of acquisition is
590	2018/02/08). It shows the typical landscape of oil palm plantations where a rectangular
591	pattern of 1000 m x 300 m is the standard management scheme.
592	Figure 5. Oil palm production curve relating oil unitary production and palms age
593	(Ismail, 2002).
594	Figure 6. A) Map showing the distribution of the estimated gain value of the 1 st order
595	polynomial interpolating the local (pixel) EVI temporal profile; B) Map showing new
596	oil palm plantation started between 2000-2018 (WGS84 Reference Frame) as classified
597	by the proposed algorithm.

- 598 Figure 7. EVI temporal profile of a generic OP pixel before (black line) and after (red
- 599 line) selective filtering.
- 600 Figure 8. A) Map of new plantations starting date; B) Map of new plantations age
- 601 (WGS84 Reference Frame).
- 602 Figure 9. Cumulative relative frequencies of absolute differences of transition matrix.
- 603 Figure 10. A) LP map (Ton FFB ha⁻¹ yr⁻¹); B) Economic value of plantation (USD
- 604 tonFFB⁻¹ha⁻¹) (WGS84 Reference Frame).
- 605