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Lopes, M, Frison, P, Crowson, M et al. (2020) Improving the accuracy of land cover classification in cloud persistent areas using optical and radar satellite image time series. *Methods in Ecology and Evolution*, 11 (4). pp. 532-541. ISSN: 2041-210X

<https://doi.org/10.1111/2041-210x.13359>

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Improving the accuracy of land cover classification in cloud persistent areas using optical and radar satellite image time series

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Abstract

1. The recent availability of high spatial and temporal resolution optical and radar satellite imagery has dramatically increased opportunities for mapping land cover at fine scales. Fusion of optical and radar images has been found useful in tropical areas affected by cloud cover because of their complementarity. However, the multitemporal dimension these data now offer is often neglected because these areas are primarily characterised by relatively low levels of seasonality and because the consideration of multitemporal data requires more processing time. Hence, land cover mapping in these regions is often based on imagery acquired for a single date or on an average of multiple dates.

2. The aim of this work is to assess the added value brought by the temporal dimension of optical and radar time series when mapping land cover in tropical environments. Specifically, we compared the accuracies of classifications based on (i) optical time series, (ii) their temporal average, (iii) radar time series, (iv) their temporal average, (v) a combination of optical and radar time series and (vi) a combination of their temporal averages for mapping land cover in Jambi province, Indonesia, using Sentinel-1 and Sentinel-2 imagery.

3. Using the full information contained in the time series resulted in significantly higher classification accuracies than using temporal averages (+14.7% for Sentinel-1, +2.5% for Sentinel-2 and +2% combining

Sentinel-1 and Sentinel-2). Overall, combining Sentinel-2 and Sentinel-1 time series provided the highest accuracies ($Kappa = 88.5\%$).

4. Our study demonstrates that preserving the temporal information provided by satellite image time series can significantly improve land cover classifications in tropical biodiversity hotspots, improving our capacity to monitor ecosystems of high conservation relevance such as peatlands. The proposed method is reproducible, automated, and based on open-source tools satellite imagery.

Key-words: cloud persistent areas, data combination, land cover mapping, remote sensing, satellite image time series, Sentinel-1, Sentinel-2

1 Introduction

Information on land cover and land cover change is key for ecosystem assessment (Cihlar, 2000). Satellite imagery has become indispensable for producing land cover maps over large areas because of its broad spatial coverage. Together with supervised classification approaches, they enable the automatic production of land cover maps. Up until a few years ago, scientists had access to imagery that was either free of charge but collected at coarse to medium spatial resolution (MODIS, Landsat), or at very high spatial resolution (a few meters or less) but costly, limiting land cover mapping to a low level of details or restricted spatial coverage. Since 2014, the availability of free satellite imagery combining both high spatial (10m) and high temporal resolutions through the Copernicus Programme has dramatically changed what can be mapped from space, increasing opportunities to both detect small elements in the landscapes and capture their seasonal variation, thereby enhancing the definition and the classification of vegetation types (Defourny et al., 2019; Gómez, White, & Wulder, 2016; Lambin & Linderman, 2006; Wulder, Hall, Coops, & Franklin, 2004).

Furthermore, the availability of co-registered optical and radar images through Copernicus facilitates the use of fusion for land cover mapping. Image fusion has often been shown to enhance land cover classification accuracy (Clerici, Calderón, & Posada, 2017; Inglada, Vincent, Arias, & Marais-Sicre, 2016; Joshi et al., 2016; Van Tricht, Gobin, Gilliams, & Piccard, 2018) because the information captured by optical and radar sensors is fundamentally different and thus complementary (Kasischke, Melack, & Dobson, 1997). In tropical and boreal areas, optical data availability is often limited by cloud cover leading to radar data being preferred to map land cover in these regions (Asner, 2001; Hoekman, Vissers, & Wielaard, 2010; Kasischke et al., 1997).

Interestingly, the information captured by high temporal resolution sensors has often been neglected in tropical environments, mainly because of the low level of seasonality characterising many of these ecosystems. Therefore, most land cover maps generated for these regions are based on single-date (when cloud-free images are available) or cloud-free composites (see e.g., Crowson et al., 2018; Erinjery, Singh, & Kent, 2018). Cloud-free composites can, however, be difficult and time-consuming to build. Similarly, the multitemporal dimension is often overlooked when combining optical and radar data, mostly because of the unavailability of radar time

66 series before the launch of Sentinel-1 in 2014 but also because dealing with time series implies more processing
67 time and computing power. Temporal compositing (Griffiths, van der Linden, Kuemmerle, & Hostert, 2013;
68 Vancutsem, Pekel, Bogaert, & Defourny, 2007) of a time series has sometimes been considered to inform
69 land cover mapping, but a large amount of temporal information is lost during this process. Hence, the
70 utility of combining optical and radar satellite image time series for land cover mapping has hardly ever been
71 assessed; known applications include the mapping of agricultural landscapes and the detection of deforestation
72 events (Hirschmugl, Sobe, Deutscher, & Schardt, 2018; Inglada et al., 2016; Kuenzer et al., 2014; Reiche,
73 Verbesselt, Hoekman, & Herold, 2015). To our knowledge, this type of approach has never been considered
74 for mapping land cover in tropical regions of conservation interest with persistent cloud cover and limited
75 level of seasonality. The aim of this study is to fill this gap in knowledge by assessing the added value of
76 preserving the temporal dimension of optical (Sentinel-2) and radar (Sentinel-1) time series. We do so by
77 comparing the outcomes of land cover classifications that consider all the images captured in a given year
78 with classifications using temporal averages. Our work is part of a collaborative UK – Indonesia research
79 project that focused on peatlands in the Jambi province, Indonesia.

80 Tropical peatlands are very important for carbon storage and are biodiversity hotspots (Wijedasa et al.,
81 2017). Peatland forests have been heavily degraded around the world through deforestation and drainage to
82 make land available for agriculture, leading to carbon release and severe and damaging fires (Miettinen, Shi,
83 & Liew, 2012; Posa, Wijedasa, & Corlett, 2011; Wijedasa et al., 2017). Efforts to restore degraded peatlands
84 – which are part of the Sustainable Development Goals – have recently been made in Indonesia, where most of
85 Southeast Asia's peatlands are located (van Eijk, Leenman, Wibisono, & Giesen, 2009). Accurately monitoring
86 land cover in the humid tropics, such as in the context of restoration efforts in tropical peatlands, is critical
87 to ensure effective conservation and restoration action, and to inform ongoing policies and strategies.

88 Here we test two hypotheses concerning the accuracy of land cover classification in cloud persistent areas
89 using multitemporal data in the optical and radar domains. As we expect our region of interest to be mainly
90 characterised by a low level of seasonality (although exceptions do exist, e.g. wetlands), the use of all the
91 dates from the optical or radar time series should not significantly improve the accuracy of our land cover
92 map compared to using the temporal average of optical or radar data (H1). Following on from the same
93 principle, the combination of optical and radar time series should have an equivalent classification accuracy
94 to the combination of the temporal averages of the optical and radar images (H2).

95 **2 Materials and Methods**

96 **2.1 Study area**

97 The study area is located along the eastern coast of Jambi province in Sumatra (Indonesia, Fig. 1). It covers
98 an area of 12,710 km² that is mostly flat. The climate is tropical humid, with an average annual precipitation
99 of 2,400 mm (Hapsari et al., 2017). Even during the dry season (June to September), monthly precipitation is
100 above 100 mm, meaning that the region is primarily subject to a low level of seasonality (Aldrian & Susanto,
101 2003; Crowson et al., 2018; Karger et al., 2016).

102 Our study area comprises both anthropogenic environments (agriculture, urban areas) and natural vege-
103 tation (peat swamp forest, mineral soil lowland rainforest, mangrove). It is mainly dominated by plantations
104 (oil palm, coconut palm, areca palm, acacia, rubber) that have replaced forests as large monoculture or small-
105 holder plantations. The eastern part of the study area is dominated by Berbak National Park (about 1,850
106 km²), which is a protected (IUCN category II), undrained peat swamp forest that supports a large amount of
107 biodiversity (Giesen, 2004). The forest is surrounded by fern-dominated scrublands which are regrowth areas
108 left unmanaged after severe fires. The Sungai Buloh Forest Reserve is located in the central part of the study
109 area and covers an area of about 120 km². Mangroves are primarily found along the coast.

110 **2.2 Reference data**

111 Reference data were generated through visual interpretation of very high spatial resolution images (2017
112 Google Earth imagery and 2017 PlanetScope scenes) using prior knowledge of the region acquired during field
113 visits. These reference data were generated in an opportunistic way but ensuring a good spatial distribution
114 of the polygons over the whole study area (Fig. 1). We primarily used the same classes as Crowson et al.
115 (2018), namely peat swamp forest, water, urban, palm trees (all combined), acacia trees, fern/scrublands,
116 bare ground; only a mangrove class was added to this original list. Mangrove polygons were digitized using the
117 USGS Global distribution of mangroves (<http://data.unep-wcmc.org/datasets/4>). In total, reference
118 data comprised 1399 polygons distributed in 8 classes (Table 1), following approximately the proportion of
119 area covered by each class over the study area, representing about 1.5 millions pixels (1.2% of the study area).

120 **2.3 Satellite imagery**

121 **2.3.1 Sentinel-2**

122 We used optical images acquired by Sentinel-2 along two different orbit paths to cover the whole study area
123 (7 tiles in total). We downloaded all the images acquired in 2017 presenting a maximum of 70% cloud cover ;
124 this resulted in 10 to 12 dates per tile. The Level L1C images (orthorectified and radiometrically corrected to

125 Top of Atmosphere reflectance) were processed to Level L2A surface reflectances (corrected for atmospheric
126 effects and slope effects) using the Sen2Cor processor (version 2.5.5) (http://step.esa.int/main/third-party-plugins-2/sen2cor/sen2cor_v2-5-5/). The algorithm provides a scene classification including
127 pixels affected by noise such as clouds and cloud shadows. Those pixels were masked and filled using a
128 temporal gap-filling method (*Image Time Series Gap Filling* application from the Orfeo ToolBox (version 6.6)
129 ; OTB (Grizonnet et al., 2017; OTB Development Team, 2018)) that replaces the masked/invalid pixels with
130 a value interpolated from the valid dates of the time series. During this process, the time series of each tile
131 were also resampled to the same temporal grid to facilitate the subsequent mosaicking. The temporal grid
132 was chosen based on the original 10 temporal acquisitions of the main (central) tile of the study area. In the
133 end, all the pixels of the study area had the same dates: 2017-02-20, 2017-03-12, 2017-07-10, 2017-07-25,
134 2017-07-30, 2017-08-19, 2017-10-08, 2017-10-18, 2017-11-22, 2017-12-22. This temporal gap-filling process
135 was done for each of the ten Sentinel-2 spectral bands at spatial resolutions of 10m and 20m (resampled to
136 10m resolution using a nearest neighbour interpolation). Finally, the tiles from the two orbits were mosaicked
137 using a mosaic technique from the OTB application (<https://github.com/remicres/otb-mosaic>) that
138 blends all the images on the overlapping areas, resulting in a seamless unique raster covering the whole study
139 area.
140

141 **2.3.2 Sentinel-1**

142 Since radar images are not affected by cloud cover, all the Sentinel-1 images acquired between February
143 and December 2017 over the study area were used to match the temporal coverage of the optical time
144 series. In total, there were 26 images, acquired every 12 days from 2017-02-03 to 2017-12-24. The images
145 were acquired over the same orbit, so no mosaicking was required. The Level-1 Ground Range Detected
146 High Resolution (GRDH) were radiometrically calibrated to the radar backscattering coefficient σ^0 for both
147 polarizations VV and VH using OTB application *SAR Radiometric Calibration* (Laur et al., 2004). They
148 were then orthorectified to correct for the geometric distortions using the OTB application *OrthoRectification*
149 (Small & Schubert, 2008). The output spatial resolution was 10m per pixel. The images were subsequently
150 converted from intensity to the logarithm dB scale, and the ratio VH/VV was computed as a third polarization.

151 Radar data are affected by speckle effects that are often filtered for land cover mapping applications. When
152 using single date images, a spatial filtering is usually done, at the cost of degrading the spatial resolution.
153 When using multitemporal images, a temporal filter such as the Quegan filter (Quegan & Yu, 2001) reduces the
154 speckle effects without affecting much the spatial resolution (Trouvé, Chambenoit, Classeau, & Bolon, 2003).
155 Simply computing the temporal average has the advantage of drastically reducing the speckle effects (Zhao
156 et al., 2019) without degrading the spatial resolution, but obviously at the cost of the temporal information.
157 In this study, we thus applied the Quegan filter on the time series to exploit the temporal information and

158 computed the temporal average from the unfiltered images.

159 **2.4 Classification protocol**

160 The classification was performed using Random Forest (RF), one of the fastest algorithms for pixel-based
161 classification with a large number of pixels and variables (Breiman, 2001; Pelletier, Valero, Inglada, Champion,
162 & Dedieu, 2016). We used RF implemented in OTB applications with the following parameters: maximum
163 depth of tree = 25; minimum number of samples in each node = 25; maximum number of trees in the forest
164 = 100, chosen following Pelletier et al. (2016) recommendations, as a good compromise between classification
165 accuracy and computation time. Pelletier et al. (2016) have shown that the RF parameters have little influence
166 on the performance of the classification. The reference dataset was split randomly but in a stratified fashion
167 into disjoint training (75%) and validating (25%) subsets, preserving the initial proportions of each class in
168 the two subsets. The split was performed at the polygon level in order to ensure an independent set of pixels
169 between the training and the validation steps (i.e., no pixels belonging to the same polygon in the training
170 and validating subsets). The resulting classification maps were sieved to eliminate isolated pixels and thus to
171 reduce the 'salt and pepper' effect associated with a pixel-based classification. Finally, the accuracy of the
172 produced land cover maps was assessed by computing the confusion matrix based on the validation subset and
173 by extracting accuracy metrics (Kappa coefficient, User's accuracy, Producer's accuracy). The training and
174 validation data are issued from the same dataset (but different polygons). As such, the resulting accuracies
175 might be slightly overestimated as they are not totally independent (Olofsson, Foody, Stehman, & Woodcock,
176 2013). However, this is not an issue here as the objective of this paper is to compare the performances of
177 different types of inputs, produced from the same set of training and validation pixels.

178 Six land cover classifications based on six different inputs were tested and compared:

- 179 • $S1_a$: annual temporal average of Sentinel-1 images in the 3 polarizations,
- 180 • $S1_t$: Sentinel-1 time series in the 3 polarizations,
- 181 • $S2_a$: annual temporal average of Sentinel-2 in the 10 spectral bands,
- 182 • $S2_t$: Sentinel-2 time series in the 10 spectral bands,
- 183 • $S1_a+S2_a$: the combination of Sentinel-1 and Sentinel-2 annual temporal averages,
- 184 • $S1_t+S2_t$: the combination of Sentinel-1 and Sentinel-2 time series.

185 For the latter two, the combination was performed by stacking both annual temporal averages / time series
186 prior to classification.

187 Additionally, an *a posteriori* fusion of classifications based on Sentinel-2 and Sentinel-1 was performed to
188 account for undetected clouds by the cloud-masking algorithm. We therefore added a supplementary "cloud"

189 class to the classifications based on Sentinel-2 data (by adding non-detected cloud polygons in the training
190 dataset), so that areas of permanent non-detected cloud cover could be identified. Then, the pixels tagged
191 as "clouds" in the subsequent classification were replaced with the results of the classification obtained with
192 Sentinel-1. The outcomes of this *a posteriori* classification are only presented for the $S1_t+S2_t$ classification
193 (named " $S1_t+S2_t$ fused $S1_t$ ").

194 Kappa coefficients associated with each pair of confusion matrices were compared to identify possible
195 significant differences in accuracies associated with our six land cover classifications (Congalton & Green,
196 1998). The test statistic Z was assessed as follows:

$$Z = \frac{|K_1 - K_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}}$$

197 where K_i is the Kappa coefficient resulting from the i^{th} confusion matrix and σ_i is the large sample variance
198 of K_i (see Congalton & Green, 1998).

199 The workflow of the preprocessing of the images and of the classification process can be found in Fig. 2.

200 3 Results

201 Contrary to our first expectation (H1), using the optical or radar time series resulted in significantly (P -value
202 < 0.001) higher Kappa coefficient than using their temporal average counterparts (82.9% for $S1_t$ against
203 68.2% for $S1_a$ and 79.0% for $S2_t$ against 76.5% for $S2_a$). Similarly, using the combination of optical and
204 radar time series improved significantly (P -value < 0.001) the land cover classification compared to using the
205 combination of optical and radar temporal averages (from Kappa = 86.6% for $S1_a+S2_a$ to Kappa = 88.5%
206 for $S1_t+S2_t$), contradicting our second hypothesis (H2).

207 In terms of per-class accuracies (see Table in the Supporting Information), most of the classes benefit
208 from the use of the time series, especially palm trees, fern, and mangrove. Most classes reached their highest
209 accuracies when combining Sentinel-2 and Sentinel-1 time series. Mangroves were not well identified using
210 Sentinel-1 compared to Sentinel-2.

211 In terms of land cover maps, the maps based on the time series look visually better (less noisy) than
212 the ones based on temporal averages (Fig. 3). Maps based on Sentinel-1 data only are riddled with 'salt
213 and pepper' noise, resulting in many misclassified pixels among classes such as forest and palm plantations.
214 In addition, Sentinel-1 data tend to confuse palm trees, mangroves and peat swamp forest (Fig. 3, top).
215 Sentinel-2 based classifications look more realistic but show big "holes" in the classes due to the presence of
216 undetected clouds, often classified as palm plantations or urban area (Fig. 3, middle). The combination of
217 Sentinel-1 and Sentinel-2 time series lead to visually better maps (Fig. 3, bottom), especially when fusing

218 $S1_t+S2_t$ with $S1_t$ (Fig. 4, bottom).

219 Overall, the best classification accuracy was obtained when replacing pixels identified as clouds by the
220 classifier using $S1_t+S2_t$ (Fig. 4, top) with results from $S1_t$ classification: the Kappa coefficient reached
221 89.4% ($S1_t+S2_t$ fused $S1_t$, Fig. 4, bottom), significantly (P -value < 0.001) improving by 1% the accuracy
222 of the $S1_t+S2_t$ classification.

223 4 Discussion

224 Our results provide for the first time a measure of the level of accuracy gained when using all the temporal
225 information of optical and radar satellite image time series to map land cover in large areas of conservation
226 value with persistent cloud cover. Despite the relatively low level of seasonality characterising most of
227 the habitats found in these landscapes, using time series significantly improved the discrimination between
228 vegetation classes compared to using annual temporal averages, suggesting that seasonal differences occur
229 among classes and should not be neglected. Combining optical and radar time series also significantly
230 improved our land cover classification, with radar data nicely complementing optical data in clouded areas.
231 Our results support the conclusions of Hirschmugl et al. (2018) who reported improved accuracy in the
232 detection of deforestation events in Malawi using time series of Sentinel-2 and/or Sentinel-1 data compared to
233 monotemporal data. Steinhausen, Wagner, Narasimhan, and Waske (2018) also found an improved accuracy
234 of land cover mapping in monsoon regions in India when increasing the number of Sentinel-1 scenes to one
235 Sentinel-2 scene, but Mercier et al. (2019) found little improvement when adding Sentinel-1 time series to
236 the one Sentinel-2 scene considered for mapping land cover in a forest-agriculture mosaic in Brazil. For these
237 two last studies, however, the use of Sentinel-2 time series was not attempted due to heavy cloud cover.

238 To our surprise, the accuracy of the classification based on radar time series was 4% higher than the
239 classification based on optical time series. More accurate classifications do not systematically generate,
240 however, "better" maps. First, maps derived from radar data are riddled with noise due to the speckle
241 effect that is typically associated with radar imagery; although filtered, this effect was still present in our
242 classification and led to numerous misclassified pixels. An additional filter could be applied to reduce this
243 effect, but it would be at the cost of spatial resolution, losing details such as drainage channels. Second,
244 and perhaps surprisingly, mangroves were not well identified using Sentinel-1, being often confused with
245 peat swamp forest. The main difference between mangroves and peat swamp forest is that mangroves are
246 submerged by sea water all year long (Wikramanayake, Dinerstein, Loucks, & Pimm, 2002). Radar data are
247 sensitive to soil wetness and were therefore expected to capture this difference well (Kasischke et al., 1997);
248 the issue here, however, is that canopy cover is very dense, meaning that Sentinel-1 C-band might not have
249 been able to penetrate it. Li, Lu, Moran, Dutra, and Batistella (2012) found that L-band provides much

250 better accuracy than C-band for land cover mapping in tropical moist regions. However, neither of them
251 could separate the types of forests investigated, showing the unsuitability of radar data alone to accurately
252 map the very similar vegetation classes found in their study area. In our study, Sentinel-2 was much better
253 at discriminating between mangrove and peat swamp forest than Sentinel-1.

254 The use of optical data in regions affected by persistent cloud cover, even as part of the fusion of optical
255 and radar data, nevertheless raises technical issues. When areas particularly affected by cloud cover are
256 detected, they can be automatically masked and complemented by radar data. In our case, however, many
257 clouds were not detected by our chosen cloud detector algorithm, which caused important problems in the
258 classification process. Specifically, the training of the classifier was made on a dataset that included "cloudy"
259 Sentinel-2 pixels associated with various land cover categories, which ultimately reduced separability between
260 classes. When looking at the generated land cover map, it resulted in holes in the land covers, as described in
261 the results section. To overcome this issue, we had to add a supplementary class "clouds" in the classification
262 involving Sentinel-2 data to identify these rogue areas. Although requiring additional steps in our overall
263 classification process (Fig. 2), this approach allowed us to better detect clouds and produced the most
264 accurate land cover map (Fig. 4, bottom).

265 The proposed method can easily be applied to large areas and reproduced in other regions because it is
266 based on freely-accessible satellite imagery and all the steps can be processed automatically in a processing
267 chain reliant on open-source software tools. Unlike previous attempts to map peat land cover in the region
268 creating a manual cloud-free composite (see e.g., Crowson et al., 2018), no manual inputs are required
269 (except to form the reference dataset, including persistent cloud cover polygons, but this step is essential to
270 all supervised classifications) ; the proposed method is thus time-saving and less sensitive to human errors.

271 Altogether, this work demonstrates how the combination of recent algorithmic advances in big data pro-
272 cessing and new earth observation capabilities associated with the development of the Copernicus programme
273 has the potential to significantly improve our ability to monitor key ecosystems in remote regions. Combining
274 optical and radar time series indeed resulted in higher accuracies for the mapping of peat swamp forests,
275 allowing environmental managers and policy makers to access up-to-date, fine scale information about peat-
276 land distribution, thereby supporting efforts to protect and restore these ecosystems. Combining optical
277 and radar time series to map land cover can seem daunting to ecologists used to classifying single optical
278 images; however, recent computational advances as well as existing spatial compatibilities between Sentinel-
279 1 and Sentinel-2 imagery significantly improve the accessibility of such approaches, and our work clearly
280 demonstrates that efforts to go beyond classical approaches do pay off. We therefore urge scientists and
281 practitioners to start exploiting the full capacity of Sentinel-2 and Sentinel-1 to monitor sensitive habitats in
282 areas of conservation interest.

283 **Acknowledgements**

284 This publication has been written with the support of the AgreeSkills+ fellowship programme which has re-
285 ceived funding from the EU's Seventh Framework Programme under grant agreement N°FP7-609398 (Agree-
286 Skills+ contract); the Toulouse-INP international mobility grant (SMI); and the Newton Fund project "En-
287 hancing the benefits of tropical peatland restoration for supporting local communities and ecosystem pro-
288 cesses", NERC Reference: NE/P014658/1.

289 **Authors' contributions**

290 ML, PLF and NP conceived the ideas and designed the methodology; BH, WDK, MC and EWT collected
291 the reference data with the help of FA; ML performed the image processing and the analysis; ML and NP
292 wrote the manuscript with feedback from PLF, MC, EWT, JKH, FA, KCH and LS. All authors contributed
293 critically to the drafts and gave final approval for publication.

294 **Data Availability**

295 The satellite images used in this study can be downloaded in the Copernicus Open Access Hub ([https://](https://scihub.copernicus.eu/dhus/)
296 scihub.copernicus.eu/dhus/). For Sentinel-2, the following search parameters were used: Sensing period:
297 2017-01-01 to 2017-12-31, Mission: Sentinel-2, Product Type: S2MSI2A, Relative Orbit Number: 118 or 75,
298 Cloud Cover %: 0 TO 70. For Sentinel-1, the following search parameters were used: Sensing period: 2017-
299 02-01 to 2017-12-31, Mission: Sentinel-1, Product Type: GRD, Sensor Mode: IW, Relative Orbit Number:
300 171. A polygon encompassing the study area (Fig. 1) was drawn manually on the search platform. The
301 images were processed using version 6.6 (doi: 10.5281/zenodo.1294917) of the Orfeo ToolBox open-source
302 software available at <https://doi.org/10.5281/zenodo.1294916> (OTB Development Team, 2018). The
303 latest version of the Orfeo Toolbox can be downloaded at <https://www.orfeo-toolbox.org>.

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Table 1: Classes used in this study (see Crowson et al. (2018) for a description of the classes).

Class	Number of reference	
	polygons	pixels
Peat swamp forest	173	353,241
Water	207	139,713
Urban	164	13,549
Palm trees	250	211,082
Acacia trees	212	360,331
Fern/scrublands	165	171,271
Bare ground	147	116,423
Mangrove	81	131,177

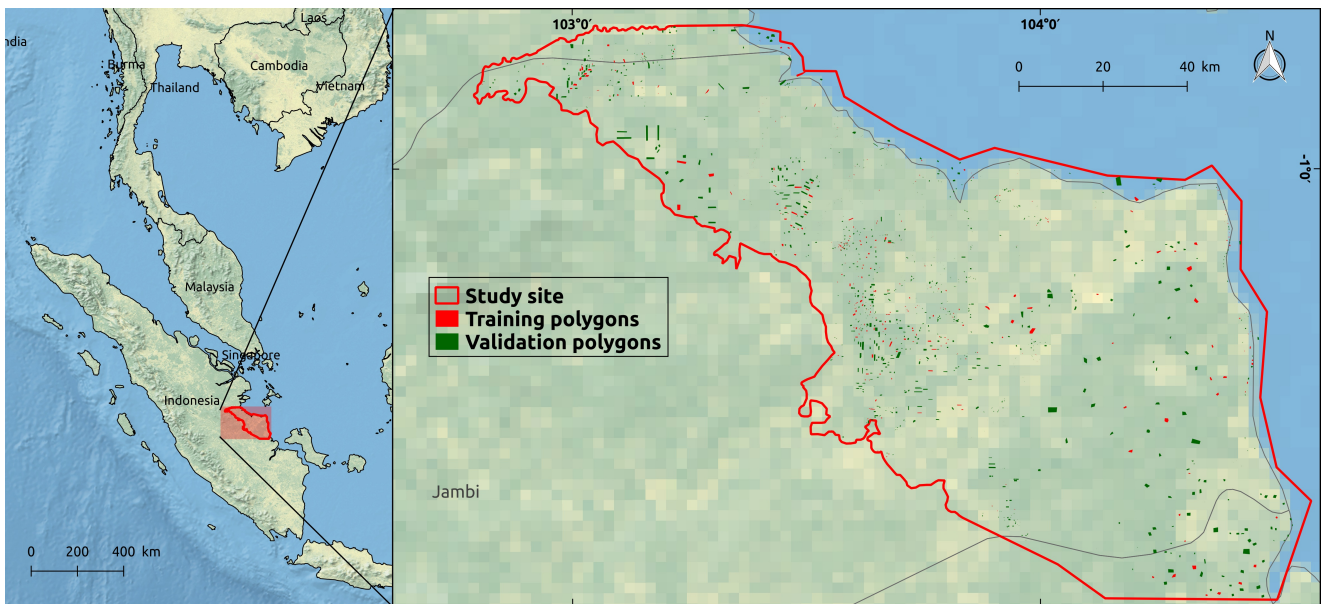


Figure 1: Location of the study area (red lines) in Jambi province, Sumatra (Indonesia) and of the reference polygons. Data: Natural Earth (<https://www.naturalearthdata.com>).

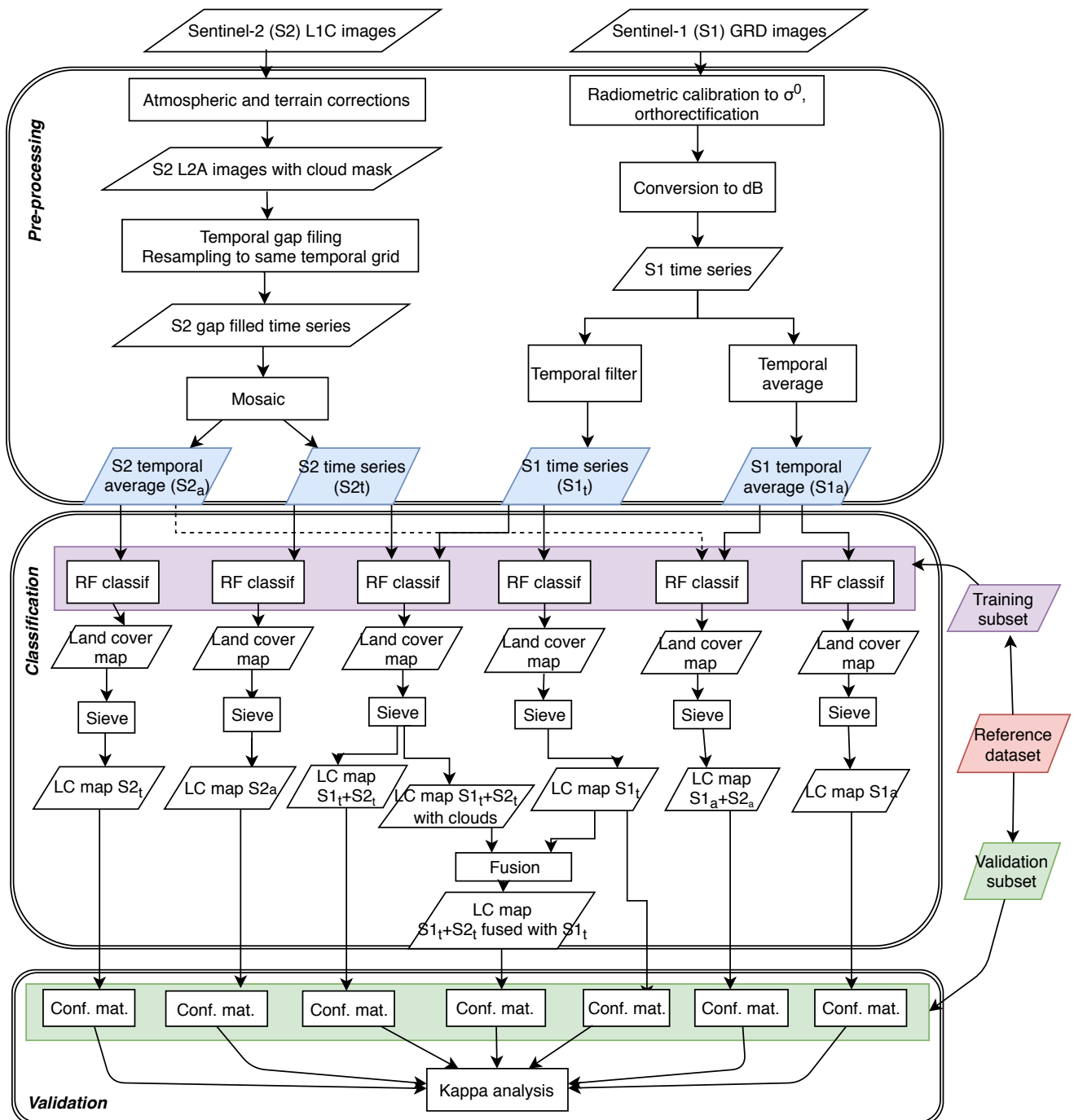


Figure 2: Workflow of the processing and the classification processes. RF classif.: Random Forest classification, LC: land cover, Conf. mat: confusion matrix.

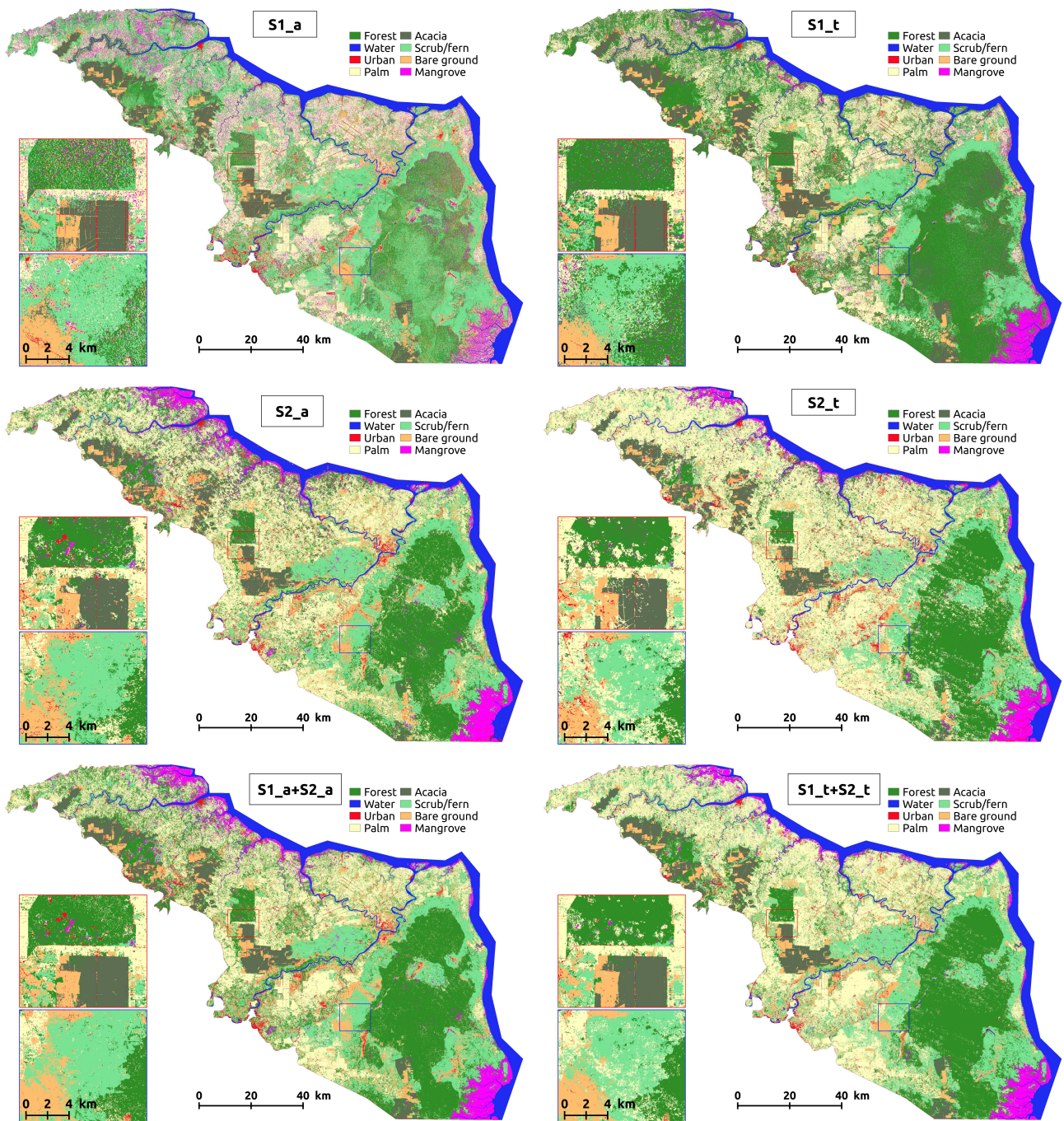


Figure 3: Land cover maps produced from Sentinel-1 ($S1_a$ (average): Kappa = 68.2%, $S1_t$ (time series): Kappa = 82.9%, top), Sentinel-2 ($S2_a$ (average): Kappa = 76.5%, $S2_t$ (time series): Kappa = 79.0%, middle) and combination of both ($S1_a+S2_a$: Kappa = 86.6%, $S1_t+S2_t$: Kappa = 88.5%, bottom).

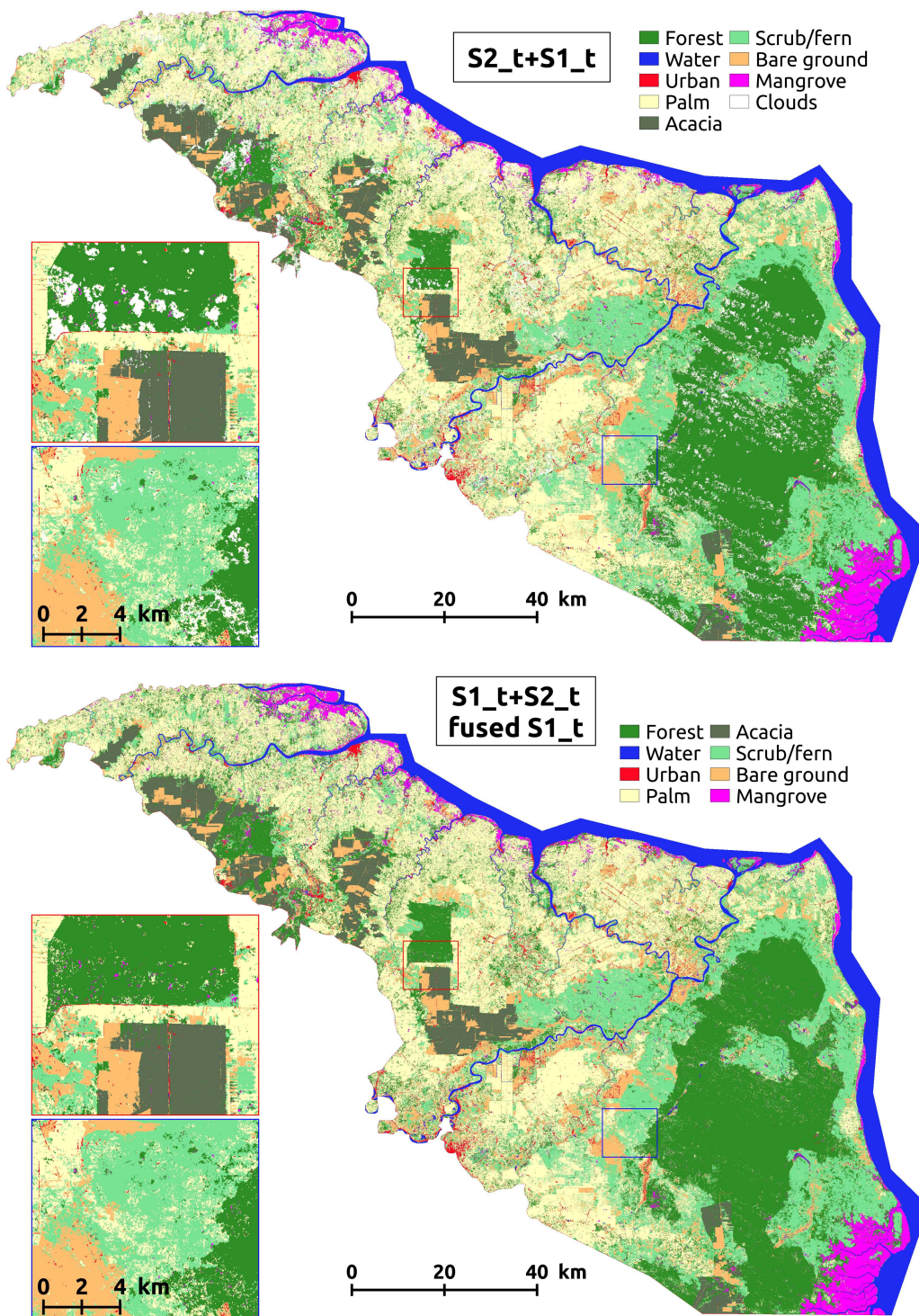


Figure 4: Land cover maps produced from Sentinel-1 & Sentinel-2 time series with cloud class (top) and clouds replaced with Sentinel-1 ($S1_t$) classification ($S1_t+S2_t$ fused $S1_t$), Kappa = 89.4, bottom).