

# PUBLISHED VERSION

Zoltan Szantoi, Scot E. Smith, Giovanni Strona, Lian Pin Koh and Serge A. Wich  
**Mapping orangutan habitat and agricultural areas using Landsat OLI imagery augmented with unmanned aircraft system aerial photography**  
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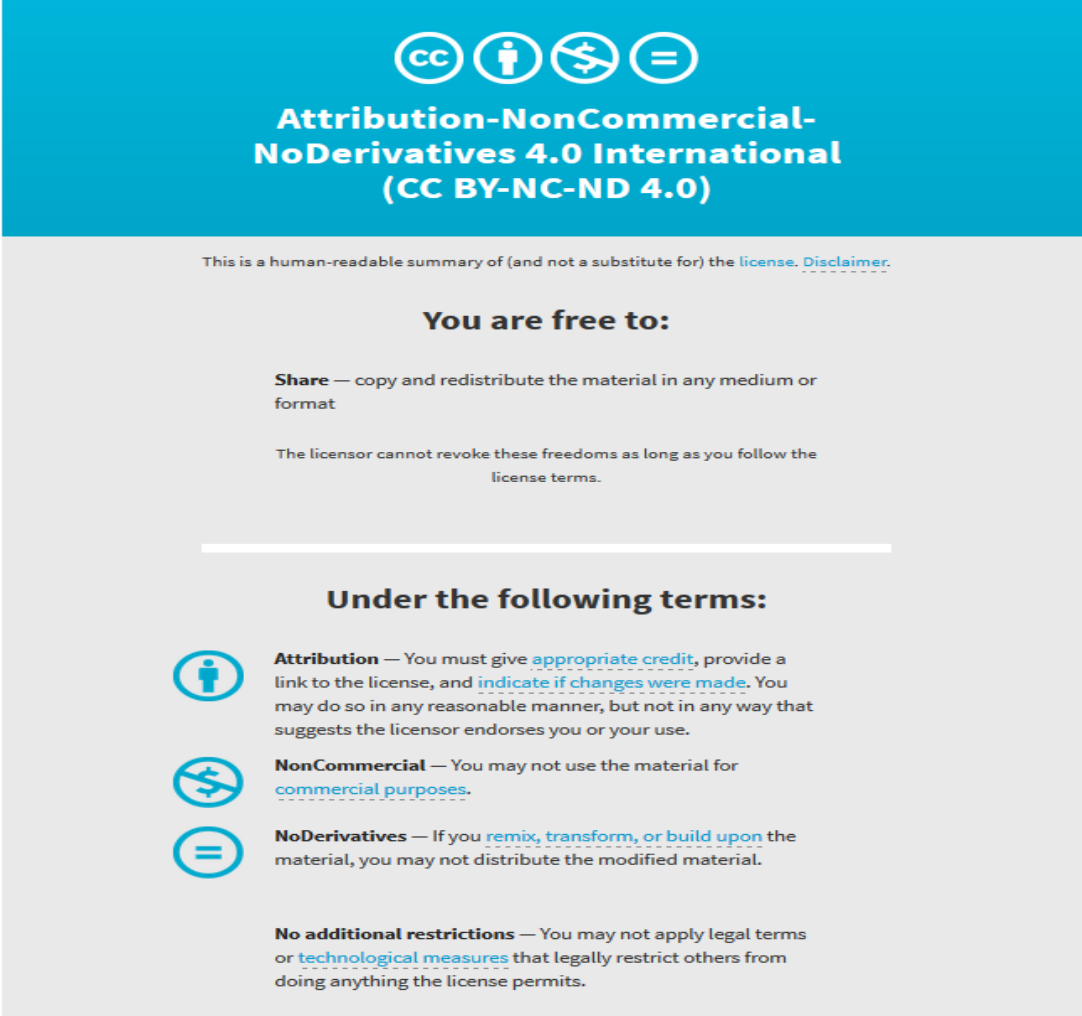
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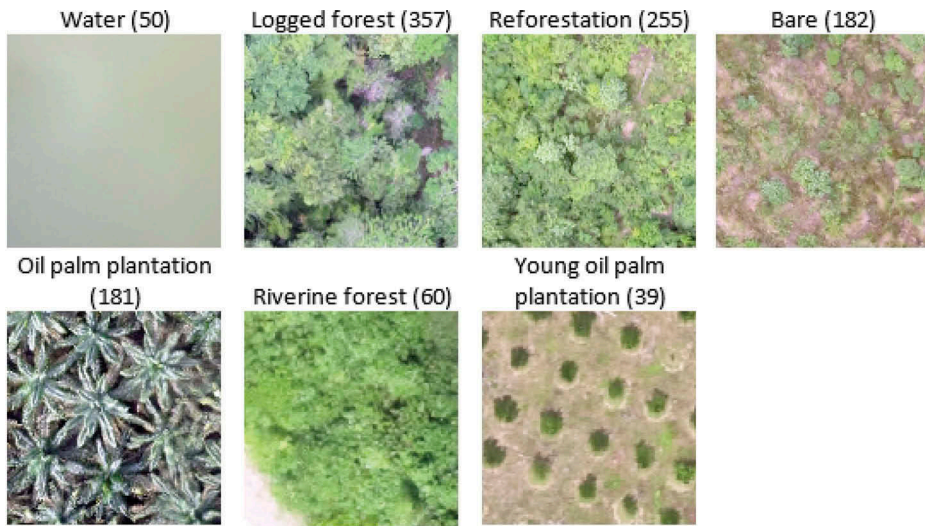












**Figure 2.** Examples of training data collected from UAS imagery. Total area of each class used to train the RF algorithm is expressed in number of Landsat pixels.

to their importance (in terms of predictive power) and to assess model accuracy (Van Der Linden et al. 2015). To train the RF algorithm, we used UAS collected data to discriminate seven different LULC classes, such as (1) *water*, (2) *logged forest*, (3) *reforested*, (4) *bare soil*, (5) *mature oil palm plantation*, (6) *riverine forest*, and (7) *young oil palm plantation*, as shown in Figure 2. According to Wich et al. (2016), the two LULC types where orangutans can be generally found are *logged forest* and the *reforested*.

### 2.2.1 Unmanned autonomous vehicle imagery

A Hornbill Survey's 'Skywalker' UAS was used in this study and is shown in Figure 3. Although the aircraft flies using a preprogrammed flight plan stored on the autopilot (<http://www.on drone.com/products/apm-2-7-autopilot>), it was under the supervision of a pilot. Skywalker's specifications are shown in Table 1. Although regulations for UAS flights in Indonesia have been recently adopted, these were not in place at the time of this study. Nevertheless, we were authorized to operate flights by the National Park Authority and took safety precautions.

Topographic relief is a critical element in planning UAS missions since these are usually conducted at low altitudes. Aceh and North Sumatra (Sumatera Utara) is characterized by rugged terrain with elevation ranging from near sea level to over 3400 m. Our surveys were conducted in relatively flat terrain, which made planning simple. Another important aspect we had to consider was the identification of suitable launching and landing areas for the UAS, taking into account vegetation and other land features, which required open, non-vegetated, or grassy areas of approximately 50 m by 100 m.

We planned the UAS flight missions with approximately 70% forward overlap and approximately 30% side overlap between photographs to generate geo-referenced mosaics (Figure 4). Flights had an altitude of 180 m above ground level, and an average









## 4. Results

Table 2 reports the error matrix of the sample counts, the weighted matrix based on the estimated area proportions, and the unbiased overall accuracy for the thematic map. The overall accuracy of the classification was 75.82% (Table 2), calculated from the error matrix, taking into account the different estimation weights, which are associated with each sample and determined by the sampling design (random sampling). The land-cover and land-use classes most strongly associated to orangutan presence/absence were detected with a consistent, high accuracy. Specifically, *reforestation* and *logged forest* both were discriminated with a producer's accuracy of 76%, while *oil palm* class (which has a fundamental importance in monitoring orangutan habitat destruction) was discriminated with a very high rate (89%).

The class corresponding to *young oil palm*, which had very small representation on the ground, was not detected. Additional classes, such as *bare soil*, were identified with approximately 76% accuracy, and small *water* bodies such as streams or tributaries were partially identified (59%) on the map (Figure 5). *Riverine forest* was poorly identified with a producer's accuracy of 23%, confused many times with the *oil palm* class. As per visual observation, based on the delivered thematic map (Figure 5), one can see that the border of the national park is fairly well maintained, at least from the north. However, a closer look can reveal (Figure 6) edge effects, where, for example, oil palm plantations (or preparation for plantation – i.e. bare land) are encroaching through the boundary. Moreover, within approximately 1 km of the border, almost no logged (i.e. primary) forest exists except for reforested areas which could also be considered degraded forest. Also, Figure 5 shows that orangutan distribution closely follows certain land-cover classes as can be seen in the eastern part of the GLNP, where protection of the park is less prevalent as bare areas and oil palm plantations encroached into its territory.

We quantified the spatial coverage of various LULC types within the predicted orangutan distribution range (Figure 5) while accounting for the corresponding detection accuracy of the thematic map (Table 3). The full extent of the orangutan's distribution, according to Wich et al. (2016), is approximately 17,870 km<sup>2</sup> for the entire region, of which roughly 6600 km<sup>2</sup> lays within the Gunung Leuser National Park. Our study area was partially within the GLNP and overlapped with the orangutan range in there (207 km<sup>2</sup>). The dominant LULC type within the orangutan range is the *logged forest* class, accounting for approximately 3/4 of the entire area (164 km<sup>2</sup>). Furthermore, the supervised classification identified a large area covered by the *reforestation* class (27 km<sup>2</sup>) and almost 9 km<sup>2</sup> of *mature oil palm plantation* and close to 5 km<sup>2</sup> *bare* classes.

## 5. Discussion

The Sumatran orangutan is threatened by habitat loss, degradation, fragmentation, and hunting (Wich et al. 2016, 2008). Frequent monitoring of its habitat is crucial to design effective conservation strategies. However, to be effective, monitoring strategies should rely on methods capable of discriminating among several land-cover and use types with a high level of accuracy in order to ensure that even small changes are promptly detected. Our results provide an important step towards this direction showing how satellite imagery at moderate spatial resolution, such as that from Landsat 8 when used

**Table 2.** Error matrices for accuracy assessment of the generated thematic map.

	Young oil palm	Bare soil	Water	Reforestation	Logged forest	Riverine forest	Oil palm	Total
Young oil palm	0	0	0	0	1	1	1	3
Bare soil	0	34	2	1	2	2	3	44
Water	0	0	6	0	2	0	0	8
Reforestation	0	3	1	50	4	1	2	61
Logged forest	0	0	0	17	95	3	3	118
Riverine forest	0	0	0	0	1	3	0	4
Oil palm	0	8	0	10	12	8	74	112
Total	0	45	9	78	117	18	83	350

	Young oil palm	Bare soil	Water	Reforestation	Logged forest	Riverine forest	Oil palm	Total	User's acc.
Young oil palm	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.002	0.00
Bare soil	0.000	0.108	0.006	0.003	0.006	0.006	0.010	0.140	0.77
Water	0.000	0.000	0.016	0.000	0.005	0.000	0.000	0.021	0.75
Reforestation	0.000	0.013	0.004	0.215	0.017	0.004	0.009	0.263	0.82
Logged forest	0.000	0.000	0.000	0.038	0.211	0.007	0.007	0.262	0.81
Riverine forest	0.000	0.000	0.000	0.000	0.004	0.012	0.000	0.016	0.75
Oil palm	0.000	0.021	0.000	0.027	0.032	0.021	0.196	0.297	0.66
Total	0.000	0.142	0.026	0.283	0.276	0.051	0.222		
Producer's accuracy	0	0.76	0.59	0.76	0.76	0.23	0.89		
<b>Overall accuracy (%)</b>								<b>75.82</b>	











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