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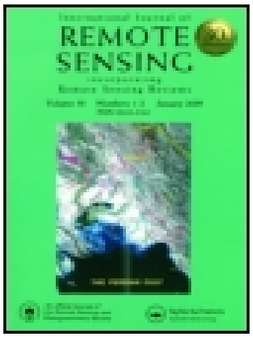

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Mapping orangutan habitat and agricultural areas using Landsat OLI imagery augmented with unmanned aircraft system aerial photography

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ABSTRACT

Conservation of the Sumatran orangutans' (*Pongo abelii*) habitat is threatened by change in land use/land cover (LULCC), due to the logging of its native primary forest habitat, and the primary forest conversion to oil palm, rubber tree, and coffee plantations. Frequent LULCC monitoring is vital to rapid conservation interventions. Due to the costs of high-resolution satellite imagery, researchers are forced to rely on cost-free sources (e.g. Landsat), those, however, provide images at a moderate-to-low resolution (e.g. 15–250 m), permitting identification only general LULC classes, and limit the detection of small-scale deforestation or degradation. Here, we combine Landsat imagery with very high-resolution imagery obtained from an unmanned aircraft system (UAS). The UAS imagery was used as 'drone truthing' data to train image classification algorithms. Our results show that UAS data can successfully be used to help discriminate similar land-cover/use classes (oil palm plantation *vs*. reforestation *vs*. logged forest) with consistently high identification of over 75% on the generated thematic map, where the oil palm detection rate was as high as 89%. Because UAS is employed increasingly in conservation projects, this approach can be used in a large variety of them to improve land-cover classification or aid-specific mapping needs.

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Introduction

Global biodiversity is declining at an unprecedented rate, mostly due to habitat destruction and hunting (Achard et al. 2014; Butchart et al. 2010). The Sumatran orangutan (*Pongo abelii*) is a species that has been mostly affected by this process, due to the conversion of lowland primary forests to oil palm, rubber tree, and coffee plantations. This, together with poaching, has reduced orangutan numbers extensively during the last century (Singleton, Wich, and Griffiths 2015). Sumatran orangutans not only have their highest densities in intact lowland forest on peat swamps and on mineral soils, but also occur at lower densities

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in selectively logged forests and primary forests at higher elevations (Wich et al. 2016). The peat swamp forests where orangutans occur are predominantly converted to oil palm plantations (78% of all forests converted), whereas forests on mineral soils are converted to agroforestry (31%), oil palm (19%), and other mixed crops (12%) as the main land-use classes (Wich et al. 2011).

The current abundance estimate for the Sumatran orangutan, which is listed as Critically Endangered by IUCN, consists of 14,600 individuals in the wild (Wich et al. 2016). This number is alarming because the orangutans are split in several smaller populations which make them more vulnerable for local extinction, especially considering that only ~25% of the Sumatran orangutan's current distribution range falls within the *Indonesian Forest Estate*, with the remaining range being unprotected. Furthermore, even in the protected areas, orangutan habitat is being lost (Wich et al. 2011).

Constant monitoring of land-use/land-cover (LULC) types aimed at tracking where changes happen (and how fast) is paramount to identify conservation priorities and to plan actions. Although map products from organizations such as the *Global Forest Watch* (http://www.globalforestwatch.org/) can aid such purpose, however, they are limited, as only forest and non-forest land cover is distinguished. In addition, such products often cannot discriminate between heavily degraded forests and primary forests (Wich et al. 2008). There is, therefore, need (and room) for improvement.

On-the-ground surveys would permit a highly accurate LULC classification, but they are arduous, time-consuming, and expensive, which makes remote sensing an obvious and preferred alternative. Clearly, there exists a trade-off between the quality (in terms of resolution) and the costs of satellite imagery. This makes monitoring LULC changes by remote sensing extremely challenging, as its effectiveness depends on both spatial and temporal resolution of the available data. Generally, lower resolution multispectral products from MODIS, MERIS, or AVHRR would allow continental scale land-cover mapping even with daily frequency; however, detailed mapping of heterogeneous landscapes is unfeasible (Hansen et al. 2016). Medium spatial resolution data, such as that from the Landsat and SPOT or from the most recent Sentinel 2, are suitable for land cover or vegetation mapping at regional the local scale (Xie, Sha, and Yu 2008). For example, Landsat (8 OLI, 7 ETM+, and 5 TM) was effectively used for large-scale forest classification (Hansen et al. 2013); however, its relatively large instantaneous field of view (30 m) limits its classification specificity, often leading to the inclusion of non-natural forests into a standard 'forest' class, and making the resulting LULC maps poor (Tropek et al. 2014; Achard et al. 2014). High-resolution imagery such as WorldView and GeoEye is excellent sources to map highly heterogeneous areas (Bassa et al. 2016); however, they have some drawback, most notably their cost and relative narrow swaths. High-resolution imagery's price is high (€17.50 km^2) (www.landinfo.com 2016) making it prohibitory expensive when mapping and monitoring as large an area as the orangutan range. However, such imagery can be used for classification validation on Landsat-based land-cover maps (Giri and Long 2014).

As an alternative to satellite imagery for training and validation purposes of medium spatial resolution-based classification is to use unmanned aircraft systems (UAS). These, when equipped with high-resolution digital single-lens reflex cameras, can capture images of high enough quality to surrogate for on-the-ground verification of land cover (Smith 2010). UAS have been successfully used in habitat and wildlife monitoring in Sumatra to identify LULC types and to monitor primate populations (Van Andel et al.

2015; Wich et al. 2015), showing great potential to increase the efficiency and reduce the cost of primate surveys and LULC change assessment.

Various machine-learning algorithms can be employed to produce LULC maps, especially when the underlying data are complex and dimensional (Rodriguez-Galiano et al. 2012). One of the most robust, yet fairly simple, algorithm compared to Artificial Neural Networks or Support Vector Machines is the utilization of classification ensembles such as the decision tree-based Random Forest (RF) algorithm (Rodriguez-Galiano et al. 2012; Bassa et al. 2016; Belgiu and Lucian 2016). As Belgiu and Lucian (2016) recently noted in a comprehensive review of the RF classifier, it is less sensitive to the quality of training samples than other machine-learning algorithms (ANN, SVM), as, generally, a great number of individual decision trees are constructed using randomly selected training samples and variables for splitting the tree nodes (Belgiu and Lucian 2016).

Here, we propose a further usage for UAS-derived images demonstrating how they can aid a supervised classification (RF) method of Landsat imagery focusing on orangutan habitat. Besides improving the value and usefulness of the Landsat derived LULC maps, this approach makes it possible to sensibly refine the detail of land-cover classes. This latter point is particularly important in the context of orangutan conservation. In a recent study, Wich et al. (2016) reported that orangutans might unexpectedly inhabit certain land covers neglected by previous studies such as logged forests and reforested cover types. Thus, detailed LULC maps such as those achievable with our proposed method, when combined with orangutan occurrence data, could sensibly improve population estimate models, considering that they rely heavily on simple land-cover classes (Wich et al. 2016) as of now.

Methodology and measurements

Study area

The study was conducted in the northeastern part of Gunung Leuser National Park (GLNP, Figure 1) in northern Sumatra, Indonesia (N4°02′21.40″; E98°03′32.71″). The park is one of the last remaining areas for Sumatran orangutans, Sumatran rhinoceros (*Dicerorhinus sumatrensis*), Sumatran tigers (*Panthera tigris sumatrae*), and Sumatran elephants (*Elephas maximus sumatranus*) (Le Saout et al. 2013). The area is mainly covered by lower and upper montane forests and freshwater rivers. Throughout the past decade, Sumatra has suffered the highest relative loss of primary forest extent (approximately 18% of land area) among all Indonesian islands (Margono et al. 2014), as it has been logged for several decades (Koh and Wich 2012).

The climate in the area is fairly uniform with temperatures between 15°C and 32°C (averaging around 25°C), while the rainfall regime ranges from humid (1500–2000 mm year^{-1}, in lowlands) to very humid (2500–3000 mm year^{-1}, in the mountains) (Laumonier 1997). We identified up-to-date orangutan distribution in the area from the map produced by Wich and his colleagues (2016) which covers the States of Aceh and North Sumatra (Sumatra Utara).

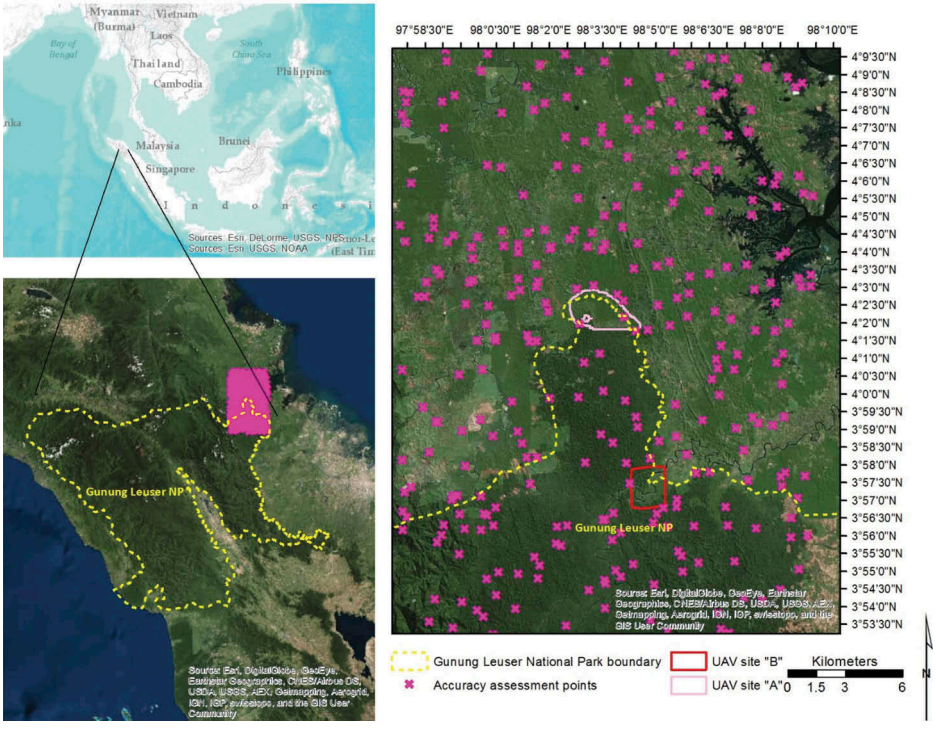

Figure 1. Study area location, Gunung Leuser National Park in Northern Sumatra, Indonesia.

Satellite imagery preprocessing and classification

We used Landsat 8 OLI imagery taken on the 7 June 2013 covering the study area. We preprocessed the scene, including georeferencing to subpixel accuracy and spectral normalization. For the latter, we corrected the spectral values by applying a 'forest normalization' algorithm (Bodart et al. 2011), where all spectral bands (values) were adjusted based on acquisition dates and reference data collected form evergreen forest cover by applying a linear shift. Although the imagery had <10% cloud cover, we masked out clouds during the preprocessing according to Szantoi and Simonetti (2013). Landsat imagery parameters (band-specific multiplicative rescaling factor, band-specific additive rescaling factor, quantized and calibrated standard product pixel values, recording date/time, and local solar zenith angle) were collected from the imagery metadata.

Following preprocessing, we used a RF supervised classifier algorithm (Belgiu and Lucian 2016) within the Environmental Mapping and Analysis Program's EnMAP Box (Van Der Linden et al. 2015) to discriminate land-cover classes. The RF classifier is a tree-based ensemble learning method that grows multiple decision trees at a time using a bootstrapping procedure (Van Der Linden et al. 2015). Individual decision trees are grown using a random subset of selected independent variables and the final classification is decided by applying a majority vote criterion to all the decision trees in the ensemble. Samples excluded from tree generation are used to rank variables according

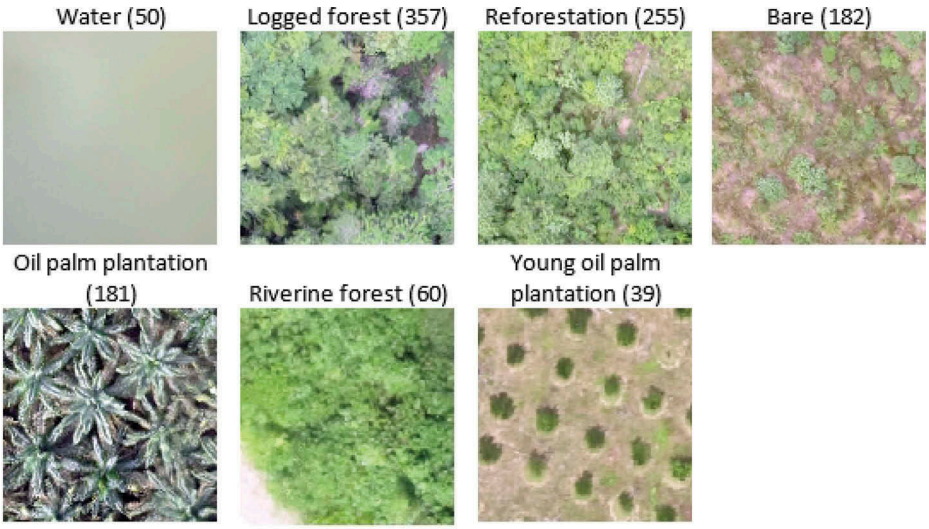

Figure 2. Examples of training data collected from UAS imagery. Total area of each class used to train the RF algorithm is expressed in number of Landsat pixels.

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*.

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.ondrone.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

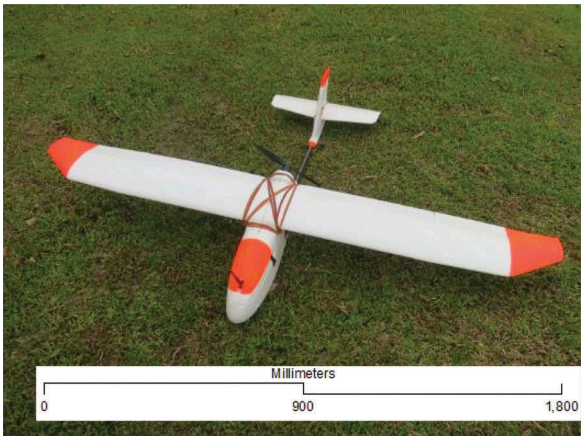

Figure 3. The skywalker UAS. The payload including the navigation unit is placed inside the frame under the wings while the autopilot and the radio antenna are accessible through the 'cockpit'.

Table 1. Specifications of the skywalker UAS.

Name	Skywalker	Motor	SunnySky 2820–800 kV
Manufacturer	Hornbillsurveys.com	**Sensor payload**	Canon S100 with 24 mm lens
Navigation system	*Strap down* GPS system	**Spectral resolution**	Red–green–blue
Autopilot	HK APM 2.7 Flight Controller	**Spatial resolution**	0.05 m at 180 m altitude
Radio control system	Futaba T 8J	**Wingspan**	1800 mm
Telemetry system	RDF 900 (ground) and 3DR 900 (air)	**Weight**	2.4 kg
Flight duration	45 min	**Cost**	±4000 USD[a]

[a]Contact corresponding author for more details.

speed of 12 m s^{-1}. Because wind makes it difficult to maintain a constant flying speed, we operated flights only in windless conditions.

The UAS sensor package was connected to a field computer through a telemetry system that allowed real-time monitoring, including direct viewing of the location of the UAS and to adjust flight parameters. The camera, a Canon S100 (12.1 MP), was mounted horizontally in the fuselage of the UAS, with the top of the camera facing forward. No filters were used and photographs were taken every 2 s using the KAP script (http://chdk.wikia.com/wiki/KAP_UAS_Exposure_Control_Script) with a ground spatial footprint of 0.05 m per pixel side.

Images were geotagged by the internal GPS of the Canon S100 camera. The photogrammetry software calculated the optimized positions of the camera, reducing the overall ground inaccuracy in GPS locations. This made it possible to superimpose satellite images and orthomosaic photographs. Since the UAS-based image collecting period corresponded to that of the Landsat scene's recording data, the seasonality did not affect our study. To produce the orthomosaic, we took into account minor deviations in flight elevation and flight attitude (pitch, roll, yaw), using the photogrammetry software Pix4Dmapper Pro (www.pix4d.com) to apply the required corrections.

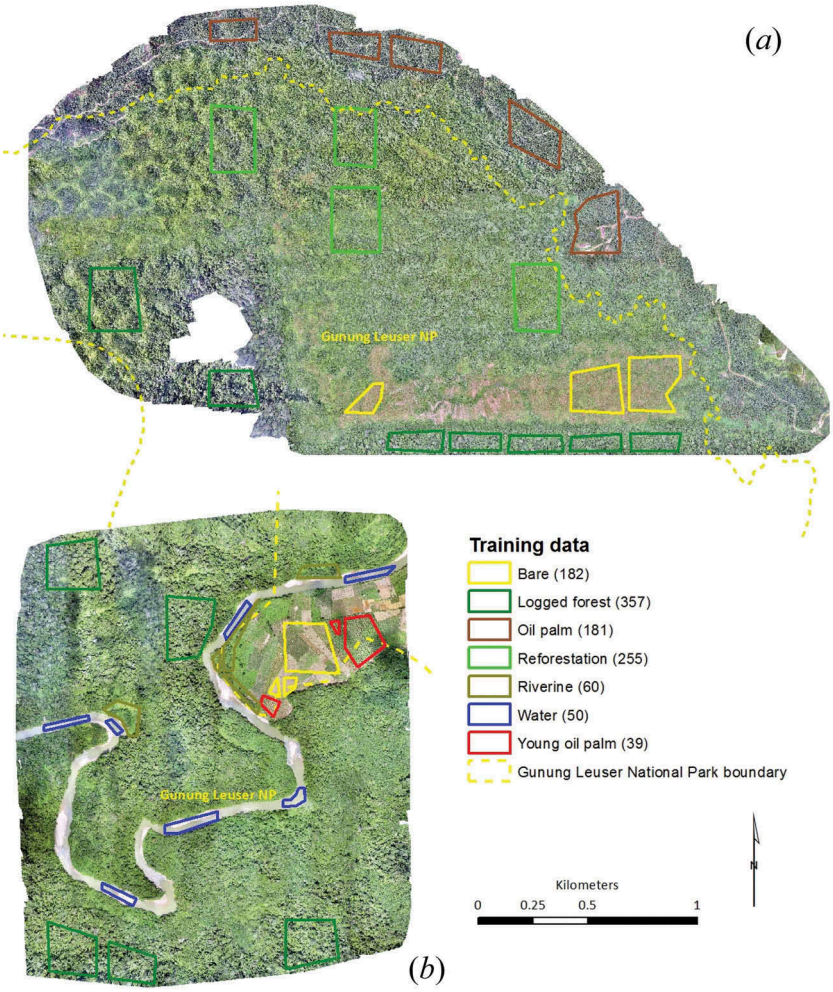

Figure 4. Geo-referenced mosaics of the two UAS sites (a and b) and the corresponding training data polygons. Total area of each class is expressed in number of Landsat pixels.

Ground data collection and accuracy assessment

While we used data collected from UAS imagery to train the supervised classifier (Figures 2 and 4), Worldview 2 and 3 (WV, DigitalGlobe Inc.) multispectral satellite imagery with a ground cell size of 1.8 and 1.24 m respectively was employed to assess the accuracy of the produced thematic map. For this, we sampled at random 350 points within the study area (Figure 1) and identified the corresponding land-cover/use classes based on the WV imagery (dates: WV-2 – 29 April 2013, centre latitude 4.505° and longitude 98.103°; and centre latitude 4.504° and longitude 97.972°; WV-3 – 21 November 2014, centre latitude 3.503° and longitude 98.055°).

Classification accuracies were summarized in a confusion (i.e. error) matrix where the user's, producer's, and overall accuracy values were calculated taking into account the

different sampling intensities within the strata, and the error-adjusted (true) areas of each LULC class (Olofsson et al. 2013) were also estimated.

We also used a Sumatran orangutan's predicted density layer based on Wich et al. (2016) to calculate the areas of various land-cover/use classes within the primate's range in our study area. The predicted density layer (Wich et al. 2016) was generated by a covariate model by using a large set of line transect data of orangutan nests in the area. An orangutan distribution (range) map (see Figure 5) for our study area was derived from the predicted density layer by extracting the actual density boundaries. The generated LULC map of the area was overlaid on the orangutan distribution map and the extent of each LULC class was calculated within the primate's distribution.

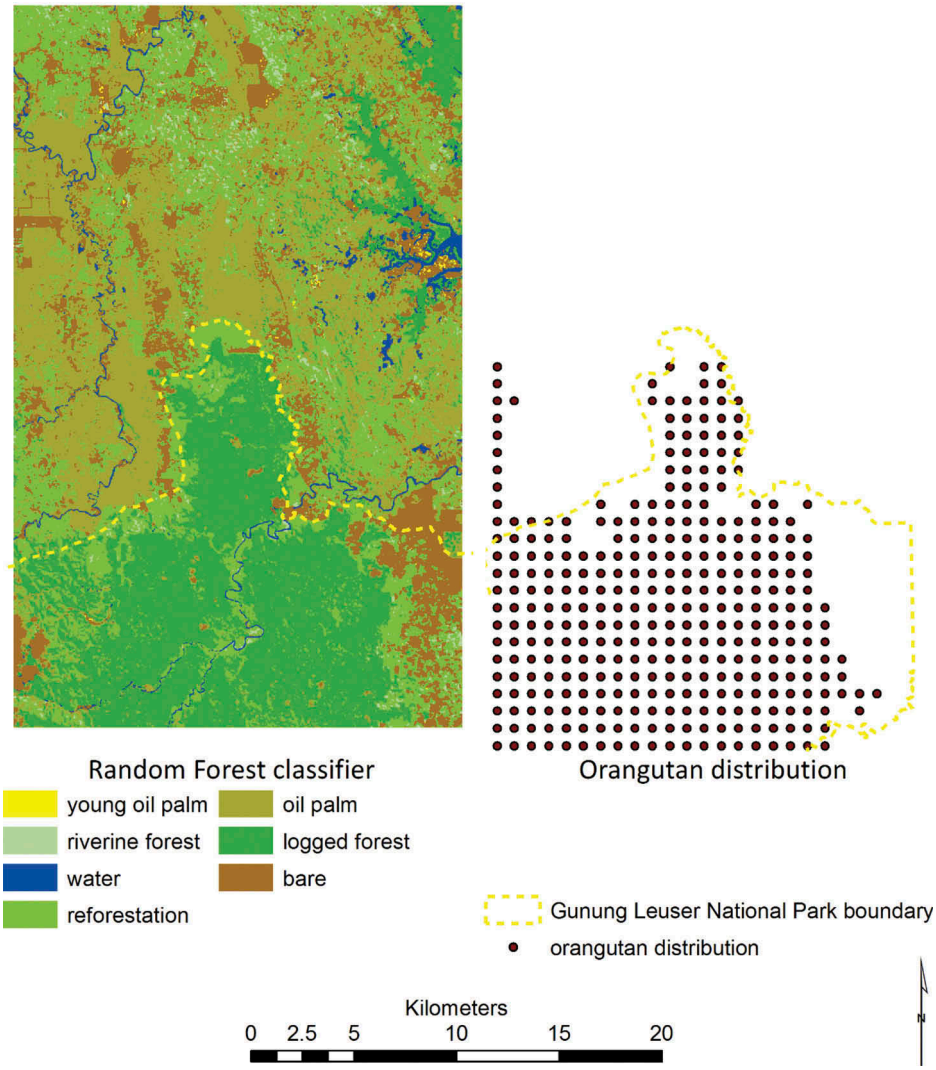

Figure 5. Land-use/land-cover map generated by the random forest classifier and the orangutan distribution map of the area.

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 form 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^2 for the entire region, of which roughly 6600 km^2 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^2). The dominant LULC type within the orangutan range is the *logged forest* class, accounting for approximately 3/4 of the entire area (164 km^2). Furthermore, the supervised classification identified a large area covered by the *reforestation* class (27 km^2) and almost 9 km^2 of *mature oil palm plantation* and close to 5 km^2 *bare* classes.

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		
Overall accuracy (%)									**75.82**

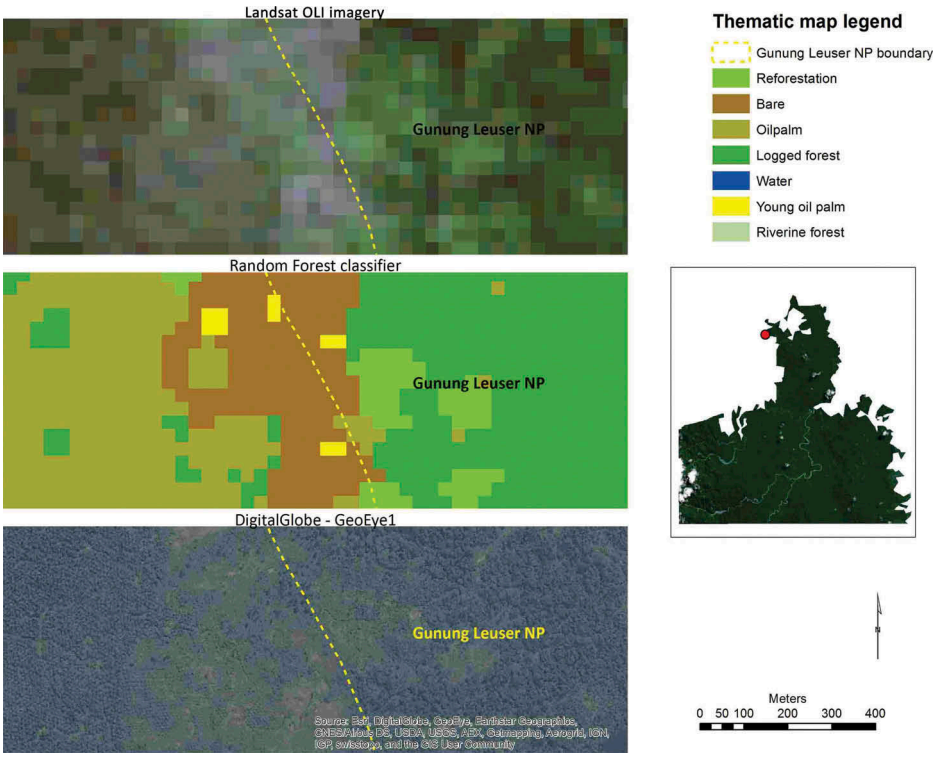

Figure 6. A detailed portion of the generated land-use/cover map compared to the Landsat and to a GeoEye scenes.

Table 3. The stratified area estimates of the mapped LULC classes in the mapped area and in the orangutan extent within the GLNP..

Land-cover/use class	Total area (km^2)	Corresponding producer's accuracy	Orangutan extent (km^2)
Young oil palm	5.15 ± 6.63	N/A	0.03
Bare soil	100.32 ± 18.92	0.76 ± 0.19	5.01
Water	14.10 ± 7.20	0.59 ± 0.51	1.57
Reforestation	151.48 ± 25.95	0.76 ± 0.17	27.13
Logged forest	217.94 ± 25.85	0.76 ± 0.12	163.92
Riverine forest	3.77 ± 4.10	0.23 ± 1.09	0.97
Oil palm	274.59 ± 27.81	0.89 ± 0.10	8.82
Total	767.35		207.45

Total areas and the producer's accuracies are presented with a 95% confidence interval.

in conjunction with UAS-derived images, can be utilized to produce accurate LULC maps including classes with high relevance for orangutan conservation, such as oil palm plantations and reforested areas (Figures 5 and 6).

When the training data based on UAS imagery was used in combination with a supervised machine learning classifier (RF, Belgiu and Lucian 2016; Rodriguez-Galiano et al. 2012), the overall accuracy was appropriate for the study objectives. More importantly, the three key classes that are difficult to identify and delineate with Landsat 8 imagery alone, i.e. *logged forest, reforested areas* and *oil palm*, were well discriminated by

our approach. It is important to note that among the mapped categories we did not include a class for undisturbed natural forest due to the fact that this area has been logged for over forty years (Knop, Ward, and Wich 2004). Yet, some of the areas attributed to the *reforestation* class are actually covered by natural forest that has regrown after clear cutting.

One of the main advantages of our approach is its cost-effectiveness, which makes it a promising tool for activities requiring frequent monitoring of LULC classes, such as wildlife conservation. Another major advantage is its timing as the UAS can be deployed virtually any time if weather permits. Thus, if experts, NGOs, and authorities perceive changes, the areas in question can be monitored quickly. Despite its low cost, the method permits us to identify multiple classes of conservation importance. Previous studies, based on Landsat imagery, attempted to discriminate oil palm plantations from forest (binary classification) (Morel, Fisher, and Malhi 2012), but achieved only approximately 70% overall accuracy. We reached and improved this level of accuracy for several LULC classes.

The possibility to obtain detailed land-cover map at a reasonable expense has the potential to greatly improve predictive models of animal abundance. The most accurate predictive model for Sumatran orangutans (Wich et al. 2016) has some accuracy limitations in distinguishing density differences between various habitats due to the fact that it is based on a 250-m resolution land-cover map (Miettinen et al. 2012) which had fewer directly related LULC classes and lower resolution than the land-cover map we have produced with our new approach.

To classify forest areas overlapping with Sumatran orangutan distribution, Wich et al. (2016) referred to only three classes (peat swamp, lowland forest, and lower montane forest), without making any distinction between these and logged forest and reforested areas. Including more land-cover classes could lead to more detailed and accurate predictive models. This is important for conservation of orangutans because research has indicated that behaviour and densities differ between logged and primary forest (Hardus et al. 2012; Husson et al. 2009; Van Schaik and Rao 1997).

Most of the previous work using UAS for wildlife studies has focused on inventories where individual animals are counted. In this study, we demonstrated that UAS images can also be confidently used in place of ground truth data to obtain a better classification (i.e. thematic map) than that provided by automated algorithms. This makes our method a valuable alternative to time consuming and costly ground truthing of LULC classes over large and remote areas.

The caveats of our approach are (1) that the medium-resolution satellite images and the UAS pseudo ground data need to be collected in a similar time frame (or at least in the same period of the year) in order to avoid potential biases due to seasonality and (2) the relative uncertain nature of flying a UAS as national regulations either does not exist or changes without prior warning. Such concerns should be taken into consideration for the next steps; following this study, would consist of developing a semi-automated LULC monitoring system aided by UAS. The classification would be conducted frequently based on freely available medium-resolution satellite imagery (satellites such as Landsat 8 and Sentinel 2) through various cloud processing platforms.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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