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Estimating land cover map accuracy and area uncertainty using a confusion matrix: A case study in Kalimantan, Indonesia

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Abstract. Remote sensing is widely used to generate land cover maps, but the maps derived from remote sensing often produce accuracy below expectations for map error. Therefore, quantifying map accuracy is essential for reporting the precision of an estimated area. This study describes a simple framework for assessing map accuracy and estimating land cover area uncertainty for a land cover changes map for Kalimantan in 2012-2018. This study compared simple random sampling and stratified random sampling to determine suitable procedures for estimating accuracy and area uncertainty. The validation relies on the visual assessment of high spatial resolution images such as SPOT 6/7 and high-resolution temporal images from Open Foris Collect Earth. Our results showed that the land cover change map assessed using random sampling had an overall accuracy of 74% while using stratified random sampling had an overall accuracy of 75%. Thus, for tropical regions with high cloud cover, we recommend using stratified random sampling. The major source of map error was in differentiating between native forest and plantation areas. Future map improvement requires more accurate differentiation between forest and plantation to better support national forest monitoring systems for sustainable forest management.

1. Introduction

Forests play a vital role in biodiversity conservation, habitat and natural resource conservation, water storage, and carbon sequestration to regulate the global climate. Over the 25 years, from 1990-2015, the global forest cover has decreased by 3% or 129 Mha, from 4128 Mha to 3999 Mha respectively, with the highest deforestation rate in 1990 at 7.3 Mha year^{-1} [1]. Tropical forest covers 44% of world forested area, yet from 2010-2015, tropical deforestation accounts for 5.5 Mha year^{-1}, and the forested area is predicted to lose at around 15% for production forest and 3% of the protected forest until 2030 [1, 2]. A broad range of bio-geographical studies, including land cover mapping and monitoring, make extensive remote sensing technology to support land management decision-making and provide information on land cover changes [3]. For example, Landsat images provide time series of optical data for decades to monitor forest extent and changes [4, 5]. However, maps produced using remote sensing often have an accuracy below rates expected for land cover maps due to positional and thematic errors [6]. Thus, an accurate assessment of the land cover map is essential to develop accountability in government

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reporting, policy-making, investment strategies and comprehend the potential consequences of map product errors.

The assessment of the accuracy of a land cover map consists of three steps: (1) specification of observation units referred to responsive design, (2) spatial sampling design and, (3) analysis of land cover classification accuracy [7, 8]. Estimating the accuracy of the total area of land classes can be determined from map accuracy assessment via a confusion matrix [9]. Estimating accuracy rates and the area, including standard errors, is essential to quantify the uncertainty attributable to sampling variability [10, 11].

The present study aims to provide a simple framework for assessing map accuracy, estimating land cover change areas, and calculating the uncertainties associated with those estimates. Two methods of sampling designs, namely simple random sampling and stratified random sampling, were compared to determine the accuracy of automatic digital land cover change maps for Kalimantan, Indonesia, from 2012-2018. The land cover change maps were produced from the Land Cover Change Analysis (LCCA) program developed by Indonesia's National Institute of Aeronautics and Space (LAPAN) to improve the Indonesia National Forest Monitoring System (NFMS) [12]. The annual LCCA maps provide an automated digital mapping method that is measurable, reportable, and verifiable. A forest and a non-forest land cover class were produced from the LCCA maps using Landsat images as the primary input data based on the multitemporal classification method. The LCCA mapped forest cover in each region of Indonesia based on different indices. However, a limitation of the LCCA maps is to discriminate between natural forests and plantations, such as oil palm and rubber plantations [13, 14]. Therefore, in addition to an assessment of forest/non-forest class accuracy and to provide assistance for governments in formulating policies that are based on information regarding land use/land cover change, this study also evaluates where incorrect classification of plantations has occurred in order to underpin future work to support robust national forest monitoring system.

2. Study Area and Methods

2.1. Study area and the land cover change map for 2012-2018

Tabalong Regency, in South Kalimantan, Indonesia, was selected as a case study and covered an area of more than 270,000 ha (Figure 1). The area varies topographically, with elevation ranging up to 1200 m and rainfall between 2000 and 3000 mm year^{-1}. In 2017, plantations in this region covered more than 72,000 ha, of which 95% were dominated by oil palm and rubber [15].

The LCCA program has produced annual land cover maps for the region since 2000 and consists of forest and non-forest classes [12]. The maps used optical Landsat images as the primary data and were processed based on steps described by [12, 13]. The LCCA mapped the forest and non-forest cover derived from different spectral indices implemented for each specific region in Indonesia based on geography and vegetation type characteristics. The LCCA mapped forest cover as an area of trees with more than 5 m height and canopy cover of more than 30%. This forest definition excludes plantations (i.e., oil palm plantations). The present study used the land cover change maps for each year from 2012-2018, with four classes of land cover change consisting of stable forest, forest loss, forest regrowth, including non stable forest.

2.2. Methods

2.2.1. Response design. There are two possible spatial units for assessing land cover maps: points and pixels/polygon [16]. This study used a 4-pixels block of a Landsat image (25 m pixel resampled) that aligns with 0.25 hectares (ha) as the minimum forested area specified for MoEF (Ministry of Environment and Forestry, Republic of Indonesia) mapping [17]. The reference data for assessing the accuracy of the land cover change maps at the block unit was obtained from the SPOT 6/7 and Open Foris Collect Earth images. The SPOT 6/7 imagery has a high spatial resolution with a 1.5 m resolution. The SPOT 6/7 images that were acquired for 2018-2019 were obtained from LAPAN (https://inderaja-

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catalog.lapan.go.id/dd4/). Additional high-resolution images were acquired from the Open Foris Collect Earth for image resolution < 5 m when the images from SPOT 6/7 were covered by clouds [18, 19].

2.2.2. Sampling design. The study compared simple random sampling and stratified random sampling methods. The simple random sampling placed each sample randomly within the study area, while stratified random sampling selected a simple random sample based on its strata corresponding to each mapping class.

All samples were identified and assessed manually using high-resolution imagery. The sample size (n = 196) was determined based on the desired confidence interval [7] using Eq.1.

$$\mathrm{n} = \frac{\hat{O}\left(1-\hat{O}\right)z^2}{e^2}$$

Where n = the sample size, and z = the percentile from a standard normal distribution using the confidence interval of 95% (z = 1.96), Ô is referred to the overall accuracy known as a proportion (targeted map accuracy), and e obtained from the desired half-width for the confidence interval Ô.

The sample size for stratified random sampling was distributed proportionally to the area of each of the four land cover classes, as per Eq.2.

$$n_s = s\frac{\hat{O}\left(1-\hat{O}\right)z^2}{e^2}$$

where n_s = the sample size per stratum, s = map proportion per stratum. The final distribution of random and stratified samples is shown in Figure 1.

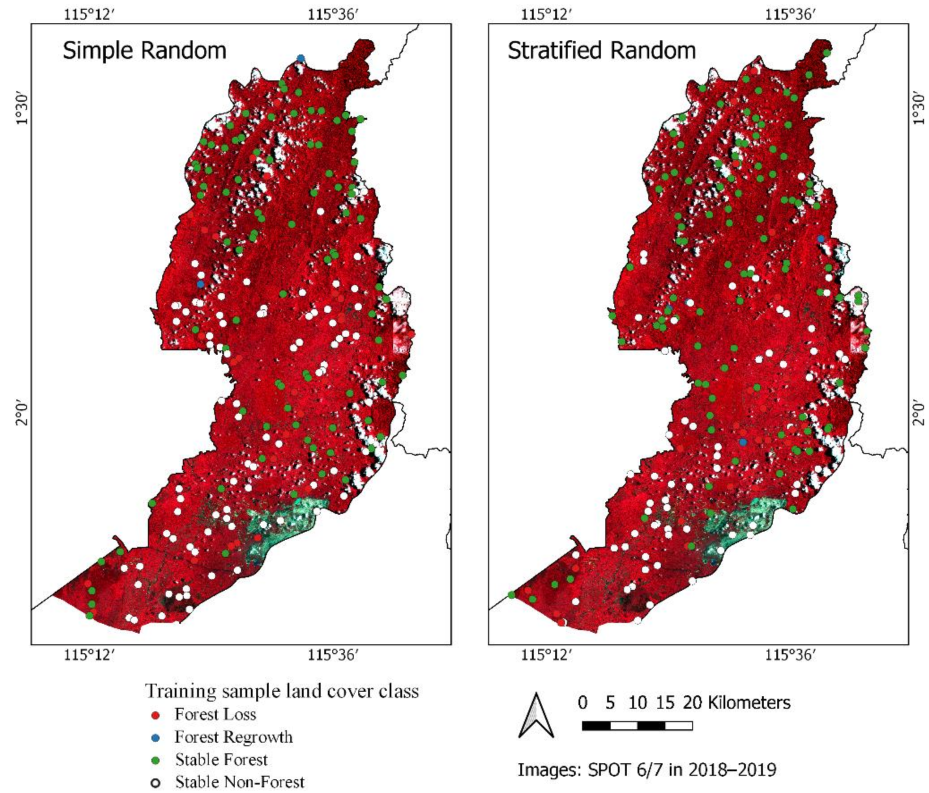

Figure 1. The location of a training sample for a simple random sample and stratified random sample distribution over the SPOT 6/7 false-color image composites in 2018-2019.

2.2.3. Analysis of the map accuracy of land cover change. Two steps were used to assess the land cover change map. Firstly, the confusion matrix, also referred to as the error matrix, was used to assess the accuracy of the maps. Secondly, the land cover change areas and their uncertainty were estimated [7, 8]. The map uncertainty was measured from a confusion matrix, standard error, with a confidence interval of 95% [7]. The confusion matrix produces information of overall accuracy (OA), user's accuracy (UA), and producer's accuracy (PA) of the land cover change map. The steps to determine the map accuracy using the confusion matrix (error matrix) and associated uncertainty are presented in Table 1 and the equations below.

Table 1. Population data for confusion matrix (error matrix) with the map data is the (M) rows, and reference data is (R) column.

		Reference data (R)				
		q	*r*	*s*	*t*	Total
Map data (M)	*q*	n_{qq}	n_{qr}	n_{qs}	n_{qt}	n_{q+}
	r	n_{rq}	n_{rr}	n_{rs}	n_{rt}	n_{r+}
	s	n_{sq}	n_{sr}	n_{ss}	n_{st}	n_{s+}
	t	n_{tq}	n_{tr}	n_{ts}	n_{tt}	n_{t+}
	Total	n_{+q}	n_{+r}	n_{+s}	n_{+t}	N

Remark: *) *q* referred to stable non-forest class, *r* referred to stable forest class, *s* referred to forest loss class, *t* referred to forest regrowth class.

The equations for assessing the map accuracy in the confusion matrix are as following:

$$n_{q+} = \sum_{q=1}^{t} n_{Mq}$$

where n_{q+} is the sum of samples classified as class *q* in the map data.

$$n_{+q} = \sum_{q=1}^{t} n_{Rq}$$

where n_{+q} is the sum of samples classified as class *q* for the data reference.

The overall accuracy of the map is determined from the sum up of the diagonal of the confusion matrix then dividing by the total sample size (n):

$$\hat{\mathrm{O}} = \frac{\sum_{q=1}^{t} n_{MM}}{\mathrm{n}}$$

The equation to determine the user's accuracy of class *q* for map data (M) is:

$$\hat{\mathrm{U}}_q = \frac{n_{qq}}{n_{q+}}$$

The equation to determine the producer's accuracy of class *q* for reference data (R) is:

$$\hat{\mathrm{P}}_q = \frac{n_{qq}}{n_{+q}}$$

The standard error and confidence interval for estimation of the uncertainty of land cover class area is determined from Table 2 where p_{qr}=n_{qr}/n has been described by [7]:

Table 2. The population of map proportion with the map data is the (M) rows, and reference data is the (R) column.

		Reference data (R)				
		Q	*r*	*s*	*t*	Total
Map data (M)	*q*	p_{qq}	p_{qr}	p_{qs}	p_{qt}	p_{q+}
	r	p_{rq}	p_{rr}	p_{rs}	p_{rt}	p_{r+}
	s	p_{sq}	p_{sr}	p_{ss}	p_{st}	p_{s+}
	t	p_{tq}	p_{tr}	p_{ts}	p_{tt}	p_{t+}
	Total	p_{+q}	p_{+r}	p_{+s}	p_{+t}	1

Remarks: *) Map proportions for the total area is 1. *q* referred to stable non-forest class, *r* referred to stable forest class, *s* referred to forest loss class, *t* referred to forest regrowth class.

The equation for calculating the map proportion using the confusion matrix for each land cover class:

$$p_{q+} = \frac{n_{q+}}{\mathrm{n}} = \sum_{q=1}^{t} p_{Mq}$$

where p_{q+} referred to the map proportion for class q in the map data.

where p_{+q} referred to the map proportion for class q in the reference data.

$$p_{+q} = \frac{n_{+q}}{\mathrm{n}} = \sum_{q=1}^{t} p_{Rq}$$

$$p_{qq} = \left(\frac{n_{qq}}{n_{q+}}\right) p_{q+} \text{ and } p_{qq} = \left(\frac{n_{qq}}{n_{+q}}\right) p_{+q}$$

where p_{qq} referred to the map proportion of class q in the land cover change map classified correctly based on the data reference.

The equation to calculate the variance of map accuracy according to the stratified random sampling outlined in [7]. The equation to estimate the uncertainty of the UA of map class q using a confidence interval of 95% (with *z* is 1.96):

$$\hat{\mathrm{S}}(\widehat{U}_q) = \mathrm{z} * \sqrt{\frac{\frac{n_{qq}}{n_{q+}}\left(1 - \frac{n_{qq}}{n_{q+}}\right)}{\left(n_{q+} - 1\right)}}$$

The estimate of the variance of the PA in map data for class q was described as follows:

$$\hat{V}(\hat{P}_q) = \frac{1}{N_{+q}^2}\left[\frac{N_{q+}^2(1-\hat{P}_q)^2\widehat{U}_q(1-\widehat{U}_q)}{n_{q+}-1} + \hat{P}_q^2 \sum_{i \neq q}^{t} N_{i+}^2 \frac{n_{iq}}{n_{i+}}\left(1 - \frac{n_{iq}}{n_{i+}}\right) / (n_{i+} - 1)\right]$$

where N_{+q} referred to the estimated marginal total number of block pixels for reference data of class q, N_{q+} referred to the estimated marginal total number of block pixels for map data of class q.

The estimate variance of the OA was described:

$$\hat{V}(\hat{O}) = \sum_{q=1}^{t} W_q^2\, \hat{U}_q(1-\hat{U}_q)/(n_{q+}-1)$$

where W_q referred to area proportion for map data for class q.

The estimate of standard error for the OA based on a confidence interval of 95% was estimated $\pm 1.96 * \sqrt{\hat{V}(\hat{O})}$ and the PA as $\pm 1.96 * \sqrt{\hat{V}(\hat{P}_q)}$.

2.2.4. Estimating the land cover change area and associated uncertainty. The method to determine the estimated land cover class areas and their respective uncertainties are set out below:
Firstly, we determine the total sample size in class q for the map data:

$$A_{Mq} = A * \ (p_{q+})$$

The land cover area for each class (hectares) was estimated as follows:

$$H_q = k * \ (A_{Mq})$$

where A referred to the numbers of sample units, H_q referred to an area for a class q (ha), k = 0.25, which corresponds to a block of 4 pixels (50 m x 50 m) as the minimum area for a single sampling.

The uncertainty of the area was estimated using the 95% confidence interval of the standard error as follows:

$$\hat{S}(\hat{P}_{+q}) = \sqrt{\sum_i W_i^2 \frac{\frac{n_{iq}}{n_{i+}}\left(1-\frac{n_{iq}}{n_{i+}}\right)}{(n_{i+}\ -1)}} = \sqrt{\sum_i \frac{W_i\hat{P}_{iq} - \hat{P}_{iq}^2}{n_{i+}-1}}$$

where W_i referred to the proportion area of map data for class i. The standard error estimated (in ha) for the class q was as follows:

$$\hat{S}(H_q) = (H_q) * \hat{S}(\hat{P}_{+q})$$

The estimated area and its uncertainty area was calculated as $H_q \pm 1.96 * \ \hat{S}(H_q)$ based on a 95% confidence interval.

3. Results and Discussion

The LCCA map showed the land cover change for Tabalong Regency from 2012-2018 (Figure 2). Based on the LCCA map, the current forested area is primarily located in the north of the region. Meanwhile, the forest loss was detected in the south of the region in the initial time series period. Thus, forest loss was detected, with scattered logging in the forested area. However, limitations of the map were that new plantations, such as rubber and oil palm plantations, were mapped as stable forests (Figure 2, zoom box).

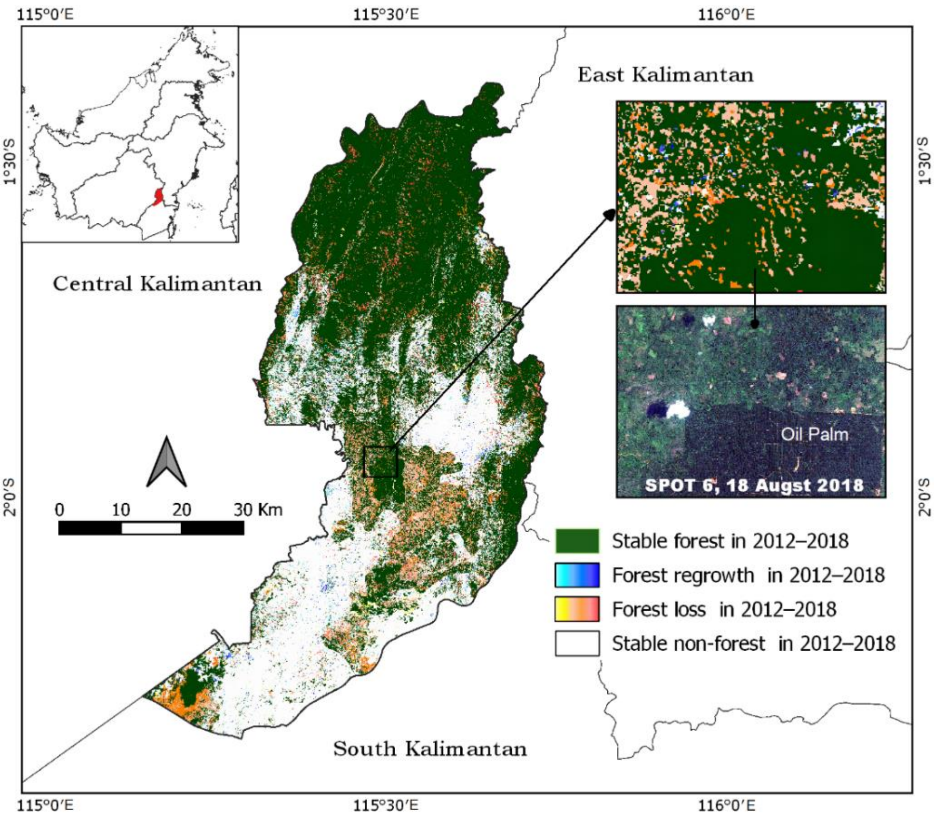

Figure 2. The LCCA map for Tabalong Regency for 2012-2018 with a zoom box of oil palm plantation.

The overall accuracy calculated using the confusion matrix based on stratified random sampling had higher accuracy compared to simple random sampling (Figure 3 and Appendix Tables A1-A2). The stratified random sampling method ensures that reference data for rare classes, such as forest regrowth, are sampled according to their proportion in the map. Stratification sampling improved the class accuracy and confidence in the estimated area due to a slightly lower variance compared to simple random sampling [20]. However, the estimated accuracy from stratified random sampling varied across land cover classes as analyzed from the producer's and user's accuracy (Figure 3).

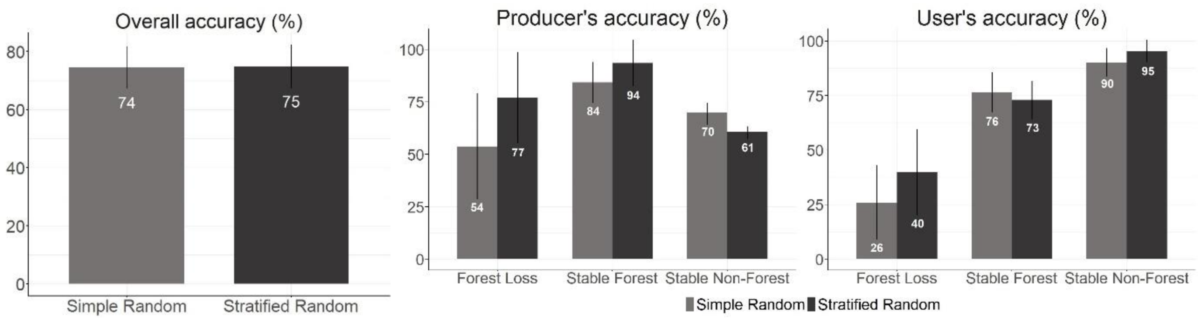

Figure 3. Map accuracy from the confusion matrix for simple random and stratified random sample methods.

Figure 3 shows that the stratified random sample for the stable forest class had high producer's accuracy (94%), but the user's accuracy was low (73%). The low user's accuracy of the stable forest class (high commission error of 27%) was primarily due to non-forested areas such as plantations being

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mapped as stable forests. In addition, the misclassification of plantations mapped as forest also led to low user accuracy of forest loss class (40%). The forest regrowth class was present on the map. However, no reference samples for forest regrowth were found in the reference data. Thus, the omission of plantation (39%) classified as the stable non-forest class led to low producer's accuracy of the stable non-forest class (61%).

The misclassification of the plantation as a forest is a common problem that has been identified in maps produced across various regions of the globe [14, 21]. This is because many of these methods have a strong reliance on optical images. While optical images are easier to interpret, the drawback is that the optical images with a moderate spatial resolution (i.e., Landsat) may cause misclassification of thick canopy crops (i.e., mature oil palm plantations). As a result, it could be mapped as a forest due to similar spectral reflectance signals. This is further complicated in regions such as the study area due to frequent clouds, which reduces the number of optical images available for analysis. Therefore, future improvements to the Indonesian NFMS method will include assessing multi-source images such as the fusion of radar and optical sensor systems to help differentiate between plantations and tropical forests [22].

The estimated uncertainty of class area calculated using the stratified random sampling reference data can be used to adjust the area estimate obtained from the map. Table 3 shows the estimation of land cover change area and associated uncertainty from stratified random sampling and the estimated land cover change area produced from the LCCA map for 2012-2018.

Table 3. Estimation of land cover change area produced from stratified random sampling and land cover change map (LCCA method) for 2012-2018.

Land cover changes category	Stratified random with standard error in parentheses (ha)*)	Map area (ha)
Stable forest	139,406 (±4807)	140,215
Stable non forest	91,097 (±1483)	91,224
Forest regrowth	5521 (±44)	5648
Forest loss	34,506 (±574)	33,442
Total	270,530	270,530

*)Uncertainty estimated using confidence interval 95%.

4. Conclusion

This study outlines a simple framework for the accuracy assessment of maps that estimate land cover change area and uncertainty with the limitation of using a small sample size. The reference sample units used to assess the accuracy assessment were 4-pixel blocks that were manually identified in high-resolution images (SPOT 6/7 and Open Foris Collect Earth). Both sampling designs, either for simple random sampling and stratified random sampling methods, were evaluated for their utility in developing the relevant accuracy statistics. The stratified random sampling used map class proportions to control sample size across the four land cover classes. In agreement with previous sampling studies, stratified random sampling improves precision regardless of smaller sample size and produces relatively lower standard errors than simple random sampling [23,24]. Therefore, the stratified sampling was preferable in this study as it resulted in higher user accuracy, producer's accuracy, with lower estimated uncertainties. Higher accuracy is required to identify the errors in maps. However, the final choice of sampling design depends on many factors, such as time interval, a complex variable of land classes, cost-effectiveness, ease of implementation, and familiarity with the method [24].

According to this study's findings, the maps' limitations identified from producer's accuracy and user's accuracy resulted in high uncertainty in forest loss and stable forest areas, primarily due to the misclassification of oil palm and rubber plantations as natural forests. Future improvement of the mapping method will involve testing the integration of radar data to assist in refining the discrimination of plantations from forest classes.

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Appendix

Table A1. Confusion matrix based on simple random sampling method in 2012-2018.

Map data	Reference data					*) User's acc. (%)	*) Producer's acc. (%)
	Stable non-forest	Stable forest	Forest loss	Forest regrowth	Total		
Stable non forest	74	6	2	0	82	90 (±6.5)	70 (±4.7)
Stable forest	16	65	4	0	85	76 (±9.1)	84 (±9.5)
Forest loss	15	5	7	0	27	26 (±16.8)	54 (±25.26)
Forest regrowth	1	1	0	0	2	0	0
Total	106	77	13	0	196	*) Overall acc. 74% (±7.29)	

*)Uncertainty estimated using confidence interval 95%.

Table A2. Confusion matrix based on stratified random sampling method in 2012-2018.

Map data	Reference data					*) User's acc. (%)	*) Producer's acc. (%)
	Stable non-forest	Stable forest	Forest loss	Forest regrowth	Total		
Stable non forest	63	2	1	0	66	95 (±5.0)	61 (±2.8)
Stable forest	25	74	2	0	101	73 (±8.8)	94 (±11.0)
Forest loss	13	2	10	0	25	40 (±19.6)	77 (±21.6)
Forest regrowth	3	1	0	0	4	0	0
Total	104	79	13	0	196	*) Overall acc. 75%(±7.5)	

*)Uncertainty estimated using confidence interval 95%.