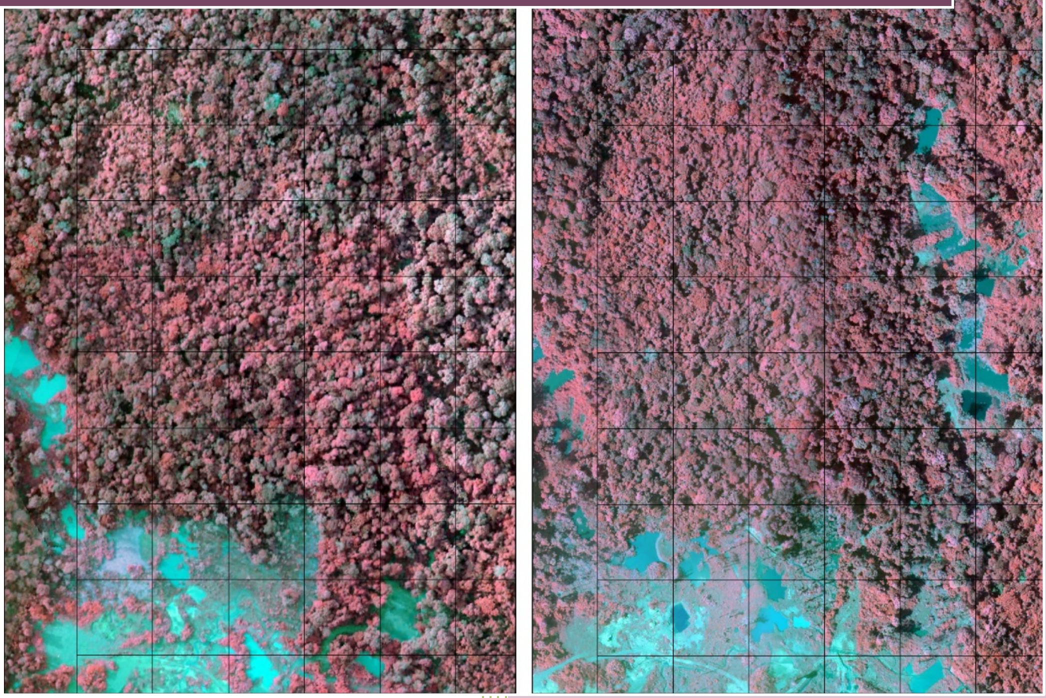
Accuracy Assessment Report Year 7 Guyana REDD+ MRVS



Durham University and

Royal School of Military Survey

Assessment Year 2017

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Guyana REDD+ Monitoring Reporting and Verification System (MRVS)

Accuracy Assessment Report

January to December 2017

Year 7

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EXECUTIVE SUMMARY

1. This report was commissioned by Indufor Asia Pacific Ltd for the Guyana Forestry Commission (GFC) in support of a system to Monitor, Report and Verify (MRVS) for forest resources and carbon stock changes as part of Guyana's engagement in the UN Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation Plus (REDD+). The scope of the work was to conduct an independent assessment of deforestation, forest degradation and forest area change estimates for the period January–December 2017. Specifically, the terms of reference asked that confidence limits be attached to forest area estimates.

2. The methods used in this report follow the recommendations set out in the GOFC-GOLD guidelines to help identify and quantify uncertainty in the level and rate of deforestation and the amount of degraded forest area in Guyana over the period January-December 2017 (Interim Measures Period – Year 7). NASA Landsat, ESA Sentinel-2, Planet-PlanetScope, and Aeroptic (aka GeoVantage) imagery was used to assess change.

3. A change analysis using two-stage stratified sampling design was conducted to provide precise estimates of forest area. Three strata were selected according to “risk of deforestation”; and, the remaining areas were designated as non-forested. The drivers (cause) of change were identified from expert image interpretation of high spatial resolution satellite imagery.

4. The estimate of the total area of change in the 12 month Year 7 period - Forest to Non-forest and Degraded forest to Non-forest is 7,722 ha with a standard error of 1,403 ha and a 95% confidence interval (4,973 ha; 10,472 ha)

5. The estimate the total area of change in the 12 month Year 7 period from Forest to Degraded forest between Y6 and Y7 is 4,764 ha with a standard error of 730 ha and a 95% confidence interval (3,332 ha, 6,196 ha).

6. One changes of 0.35 ha detected with a sample located within the boundary of the Intact Forest Landscape. This was interpreted as caused by shifting agriculture.

7. The sample-based estimates for land cover class areas for December 2017 are as follows:
    a. Forest = 18,968,406 ha
    b. Degraded forest = 164,468 ha
    c. Non-forest = 1,915,067 ha + 990,000 ha (in the zero risk stratum) = 2,905,067 ha
    d. Note that the total area of Guyana in the sample-based estimates is 1.5% different from the GIS-based area because the samples use a 1 km by 3 km grid that intersects with the national boundary polygon.

1 AREAS OF ACTIVITY

1. To assess Year 7 deforestation, taking note of IPCC Good Practice Guidelines and GOFC/GOLD recommendations.
2. To outline a methodology for accuracy assessment including an outline of the (1) sample design, (2) response design, and (3) analysis design.[1] For the design component, reference data to be used should be identified, and literature cited for methods proposed. The design must ensure representativeness of the scenes selected for analysis. The sampling specifications used must be stated.
3. To support independent verification of the REDD+ interim measures and national estimates (Gross Deforestation, Intact Forest Landscape, Extent of Degradation associated with new infrastructure, and emissions from forest fires – referred to in the context of the Joint Concept Note between the Governments of Guyana and the Kingdom of Norway, including initial interim results, with a priority being on gross deforestation and the associated deforestation rate (i.e. change over time) and assessing their error margins/confidence bands, and providing verification of the deforestation rate figure for Year 7 as an area change total and by driver.
4. To conduct an independent assessment of the deforestation mapping undertaken by the Guyana Forestry Commission and comment on the attribution of types of changes e.g. agriculture, mining, forestry and fire. Make recommendations that can be used to improve efforts in the future. This assessment should be done with the recognition that "best efforts" will have to be applied in situations where there is a challenge in terms of availability of reference data. The error analysis should highlight areas of improvement for future years to decrease uncertainties and maintain consistency. Additionally, the assessment should also consider the quality on how missing data were treated for national estimation (if this is observed to be the case). It is required that real reference data is used either from the ground, ancillary data (e.g. for concessions), and/or high resolution imagery.
5. For 2017 (year 7), forest degradation was not interpreted and mapped from satellite imagery to create a 'forest degradation' GIS layer. Instead, forest degradation was estimated from a two-stage statistical sample with randomisation of the first stage. The role of Durham University was to carry out a full quality assurance and quality control assessment on the data generated by the GFC mapping team.
6. To use the sample data to estimate the extent of forest degradation for Year 7 for the whole of Guyana and to report error margins/confidence bands, and provide verification of the forest degradation rate for Year 7 as an area change total and by driver. This assessment is done with the recognition that "best efforts" will have to be applied in situations where there is a challenge in terms of availability of reference data. The error analysis highlights areas of improvement for future years to decrease uncertainties and maintain consistency. Additionally, the assessment considers the effect of missing data for national estimation. It is required that real reference data are used either from the ancillary map data (e.g. for concessions), and the data acquired specifically for accuracy assessment including high spatial resolution imagery.

[1]GOFC GOLD Sourcebook (2016) Section 2.7.

2 AREA REPRESENTATION

The total land area for Guyana is 21,127,762 hectares, calculated from the national boundary Shapefile provided by GFC in 2014. The digital maps contained in the report were obtained from the Guyana Forestry Commission (GFC), the Guyana Land and Surveys Commission (GL&SC). All maps use the WGS 84 datum and are projected to UTM Zone 21N.

2.1 Forest Area

Land classified as **forest** by GFC follows the definition from the Marrakech Accords (UNFCCC, 2001). Under this agreement forest is defined as: a minimum area of land of 1.0 hectare (ha) with tree crown cover (or equivalent stocking level) of more than 10-30% with trees with the potential to reach a minimum height of 2-5 m at maturity in situ.

In accordance with the Marrakech Accords, Guyana has elected to classify land as forest if it meets the following criteria:

- Tree cover of minimum 30%
- At a minimum height of 5 m
- Over a minimum area of 1 ha.

The forest area was mapped by GFC / IAP by excluding non-forest land cover types, including water bodies, infrastructure, mining and non-forest vegetation. The first epoch for mapping is 1990, and from that point forward land cover change from forest to non-forest has been mapped and labelled with the new land cover class and the change driver. GFC have conducted field inspections and measurements over a number of non-forest sites to verify the land cover type, the degree of canopy closure, the height of the vegetation and its potential to regenerate back to forest.

The assessment in this report does not look at the GFC / IAP mapping, it is an independent analysis. For reference we note that the Y7 mapping process involves a systematic review of Landsat and Sentinel data. Details of the GFC / IAP Y7 mapping are explained in the Standard Operating Procedure for Forest Changes Assessment. Areas mapped as deforested during the period 1990-2009 are used to establish the *deforestation rate* for the benchmark reporting period.

The purpose of this report is to build upon the estimates of deforestation established for Years 1-5 of the Norway-Guyana agreement and to quantify the precision of the estimate of deforestation and forest degradation observed in the Year 7 period. A second task is to identify the processes (drivers) that are responsible for deforestation and degradation, and where possible to estimate the precision of area estimates.

3 SAMPLING DESIGN FOR VERIFYING YEAR 6 TO YEAR 7 FOREST CHANGE

3.1 Change sample design

The Year 7 assessment for gross deforestation and forest degradation in Guyana used a two-stage stratified random sampling design. Stratification was based on past patterns of deforestation from Period 1 (1990) through to Year 4 (Dec 2013), where the primary drivers of land cover change are alluvial gold mining, logging, anthropogenic fire, agriculture and associated infrastructure including roads.

The assessment is guided by established principles of statistical sampling for area estimation and by good practice guidelines (GOFC-GOLD, 2016, UNFCCC Good Practice Guidance (GPG) and Guidelines (GL)). The purpose of stratification is to calculate the within-stratum means and variances and then calculate a weighted average of within-stratum estimates where the weights are proportional to the stratum size. Stratification will reduce the variance of the population parameter estimate and provide a more precise estimate of forest area and forest area change than a simple random sample.

The sampling design and the associated response design are influenced by the quality and availability of suitable reference data to verify interpretations of the GFC Forest Area Assessment Unit (FAAU). In Year 3, 4 and 5 the GFC Forest Area Assessment Unit (FAAU) used RapidEye as the primary mapping tool and so the whole country was mapped from multiple looks of orthorectified RapidEye resampled data to 5m pixel size. For Y7 the GFC Forest Area Assessment Unit (FAAU) used Landsat and Sentinel-2 imagery as the primary mapping tool. The Y7 response design used PlanetScope, GeoVantage, and Sentinel-2 imagery as an appropriate fine-resolution source of data to validate land cover changes in all but the low risk of change areas where assessment was based on interpretation of Sentinel-2 and Landsat data.

For Guyana, the established MRV protocol is for the entire country to be remapped on an annual basis, and so a forest change map will be generated from wall-to-wall coverage of satellite data. To assess the accuracy of land cover change statistics an independent reference sample is needed. The focus of the independent assessment places emphasis on inference, that is optimising the precision of the change estimates. Therefore, we generate an *attribute change sample* as the reference data to estimate gross deforestation and forest degradation area.

A change sample for reference data will:

1. have a smaller variance than an estimate of change derived from two equivalently sized sets of independent observations, provided the correlation coefficient is positive;
2. increase the precision of the change estimate by virtue of the reduction of the variance of estimated change;
3. despite its obvious advantage, encounter practical and inferential problems if resampling the same areas proves difficult, or if, as time passes, the sample or the stratification of the sampling scheme, is no longer representative of the target population (Cochran 1963; Schmid-Haas, 1983);
4. for the same sample size, require no additional resource but allow both map accuracy and area estimation to be performed;
5. be an alternative to wall-to-wall mapping and may be preferred because of lower costs, normally smaller classification error, and rapid reporting of results;
6. have value when assessing any additional forest change map product such as the University of Maryland Global Change map 2000-2016 or any annual updates published by Maryland.

The desired goal of this validation is to derive a statistically robust and quantitative assessment of the uncertainties associated with the forest area and area change estimates.

Several factors potentially impact on the quality of forest mapping (GOFC GOLD, 2016), namely

- The spatial, spectral and temporal resolution of the imagery
- The radiometric and geometric pre-processing of the imagery
- The procedures used to interpret deforestation, degradation and respective drivers
- Cartographic and thematic standards (i.e. minimum mapping unit and land use definitions)
- The availability of reference data of suitable quality for evaluation of the mapping

The Standard Operating Procedure for Forest Change Assessment (GFC and Indufor Ap Ltd, 2015) outlines approaches used to minimize sources of error following IPCC and GOFC-GOLD good practice guidelines as appropriate.

The verification process used follows recognised design considerations in which three distinctive and integral phases are identified: response design, sampling design, and analysis and estimation (Stehman and Czaplewski, 1998).

3.2 Response Design

Table 3-1 summarises the data available to validate the deforestation and forest degradation change estimates for 2017, that is the end of 2016 (year 6) and the end of 2017 (year7). It also specifies the areal coverage of the imagery used for change assessment.

Table 3-1: Data sources used for Validation (Application: Forest Change Assessment)

Dataset used	Provider	Sensor	Spectral Range	Date of Acquisition	Pixel size (m)	Area (ha)	% of Guyana
RGB and CIR aerial photography	GeoVantage	Four channel multi-spectral sensor	Visible and NIR	Nov-Dec 17	0.25-0.60	583,949	2.76
PlanetScope	Planet	Four channel multispectral sensor	Visible and NIR	Aug-Dec 16 Aug-Dec 17	3	3,898,900 2,890,883	18.4 13.7
Sentinel-2	ESA	Four channel multispectral sensor (at 10m)	Visible and NIR	Aug-Dec 16 Aug-Dec 17	10	19,347,200	91.5
Landsat	USGS	ETM+ and ALI	Visible and NIR	Aug-Dec 16	30	21,127,762	100

A critical component of any accuracy assessment is the need for appropriate reference data (Herold et al, 2006; Powell et al 2004). It is often the case that reference data itself contains errors and is not a gold standard and at least one study reports large differences of the order of 5-10% between field-based and remotely sensed reference data (Foody, 2010; Powell et al. 2004). Therefore, a key aspect of the response design is to use reference data that allow forest / non- forest land cover to be classified with certainty. Year 7 deforestation and degradation was mapped by the IAP/GFC team from Sentinel-2 and Landsat imagery, while the accuracy assessment primarily used PlanetScope and GeoVantage imagery supplemented by the detailed reinterpretation of Sentinel-2 satellite imagery in parts of Guyana that were within the Low Risk stratum, and occasionally Landsat where there were clouds in Sentinel.

For 2017, as with 2015-16, forest degradation was not mapped wall-to-wall across Guyana. The level of degradation was estimated from a change analysis of reference data using a two-stage stratified sample with randomisation of the first stage sample transects. The change analysis interpreted land cover at two time periods using the best available reference data - primarily PlanetScope and GeoVantage imagery supplemented by reinterpretation of Sentinel-2 and occasionally Landsat where other imagery was obscured by clouds.

The degradation analysis was also carried out by the GFC mapping team (six persons) using a rules-based approach that is described in the Standard Operation Procedure for degradation assessment (see Appendix 8 of the MRVS Report). Note that the definition of forest degradation requires the interpreter to make a quantitative assessment of the area of forest lost and to record the loss as a proportion of each hectare sample analysed. Even though the interpreter has access to the area 'measure tool' within ArcMap, any misinterpretation or miscalculation of change is most likely to arise from human-error or interpretation using poor quality imagery or areas partially obscured by cloud or cloud shadow. In addition to assessing evidence for land cover change, the interpreter is required to assign a driver to every sample area that exhibits change. The choice of change driver is selected from a drop-down menu of known reasons for deforestation and forest degradation. However, the process of selecting a change driver is subjective and depends on the knowledge of the interpreter and the level of care taken in interpreting the imagery and with following the definitions / rules and respecting the exclusions (e.g. Table 3-2) specified in the SOP.

Table 3-2 Year 7 Deforestation and Forest Degradation Assessment Exclusions

Reference	Criteria
1	Land use change that occurred prior to 1 January 2016 or after 31 December 2017
2	Roads less than a 10 m width.
3	Naturally occurring areas – i.e. water bodies
4	Cloud and cloud shadow

The following sections provide a summary of the datasets available and the way they were used for the accuracy assessment.

3.3 GeoVantage

GeoVantage is an aerial imaging camera system mounted externally to a light aircraft, in our case a Cessna 172. The camera system comprises a multi spectral sensor, capturing red, green, blue, and near infrared spectral bands. The spatial resolution of the imagery depends on the altitude that the data is captured. For this project the operating altitude ranged from 2000 to 5000 ft and the resultant imagery ranged from a pixel size of 25 cm to 60 cm. Deriving a change sample based of aerial imagery over tropical forests is a challenging task given the constraints of weather, cloud cover and navigating the exact same flight path as the previous year. GeoVantage imagery was acquired in November-December 2015 over approximately 132 sample areas in the High and Medium Risk strata. Acquisition was repeated in September-October 2017, again acquiring imagery in the High and Medium Risk strata for 132 sample transects. These very high resolution images are helpful for confirming the status of sample areas at the end of the assessment period, particularly for identifying areas of forest degradation because the area of forest loss can be measured easily from the imagery using ArcGIS tools.

The GeoVantage data were acquired by Agrisat S.A who also performed image mosaicking, rectification and colour balancing. The majority of GeoVantage imagery for 2015 and 2017 were of good geometric quality; some frames exhibited saturation which made land cover interpretation difficult.

3.4 **PlanetScope**

PlanetScope data were downloaded from the Planet Explorer Beta GUI tool that can be used to search Planet's catalog of imagery, view metadata, and download full-resolution images[2].

PlanetScope is a swarm of 120 micro (10cm x 10cm x 30cm) satellites orbiting the Earth at 475 km altitude, and offering the capability of daily revisit. The first three generations of Planet's optical systems are referred to as PlanetScope 0, PlanetScope 1, and PlanetScope 2. PlanetScope 2 has a 4-band multispectral imager (blue, green, red, near-infrared) with a Ground Sample Distance of 3.7 m. The radiometrically-corrected orthorectified product (that was used in this project) is resampled to 3m.

The radiometric resolution is 12-bit and sensor-related effects are corrected using sensor telemetry and a sensor model. The bands are co-registered, and spacecraft-related effects are corrected using attitude telemetry and best available ephemeris data. Data are orthorectified using GCPs and fine DEMs (30 m to 90 m posting). While in 2016 the PlanetScope imagery was found to be of varied quality with different radiometric integrity displayed by different sensors, and on some occasions the imagery had a positional offset, in 2017 the PlanetScope imagery was substantially better both radiometrically and geometrically.

3.5 **Sentinel-2**

The Sentinel satellites are launched by ESA in support of the EU Copernicus programme. Sentinel-2A and -2B carry an innovative wide swath high-resolution multispectral imager with 13 spectral bands primarily intended for the study of land and vegetation. The bands vary in spatial resolution, with four bands (Blue, Green, Red, and NIR) at 10m, six bands (four in NIR and two in SWIR) at 20m, and three bands (Blue, NIR and SWIR) at 60m. Although data are processed to different levels, only Level-1C (orthorectified product) is provided to users. The Sentinel Toolbox[3] can then be used to generate a Level-2A (Bottom of Atmosphere reflectance product). Although the pixel size of 10m is not as fine as PlanetScope, the Sentinel-2 radiometric resolution was found to be superior, thus providing a clearer (but not finer) land cover image.

GFC acquired multiple Sentinel 2 scenes to cover the whole land area of Guyana for Aug-Dec 2016 and Aug-Dec 2017. Multiple scenes area required to cope with cloud cover.

[2] http://www.planet.com/explorer (last accessed: December 2017)
[3] https://earth.esa.int/web/sentinel/toolboxes/sentinel-2 (last accessed: December 2017)

3.6 **Sampling Design for Change Analysis**

The sampling design refers to the methods used to select the locations at which the reference data are obtained. To assess the area and rate of deforestation a two stage sampling strategy with stratification of the primary units was adopted. First a rectangular grid of 5 km by 15 km in size was created within the spatial extent of the country's national boundary[4]. The shape was selected to assist with the collection of North-South orientated strips of aerial GeoVantage imagery as this shape minimises the cost of acquisition of the imagery. Gridding resulted in 2837 rectangles; note that only rectangles with a centroid within the Guyana national boundary were selected.

As the area of the country is large, and deforestation is observed to be clustered around relatively small areas of human activity, it is efficient to adopt a stratified sampling framework rather than use simple random or systematic sampling (Gallego, 2000; Foody, 2004; Stehman, 2001). For each stratum, sample means and variances can be calculated; a weighted average of the within stratum estimates is then derived, where weights are proportional to stratum size. In this case, the goal is to improve the precision of the forest (or deforestation) area using a stratum-based estimate of variance that will be more precise that using simple random sampling (Stehman and Czaplewski, 1998; Stehman, 2009; Potapov et al., 2014).

Strata are based on actual observations of deforestation (particularly Years 1 to 4). The method first selected the grid rectangles that intersected deforestation events. For every year of deforestation the value 1 (one) was given. If no event was recorded then the value 0 (zero) was given. For example, the rectangle with value 0011 intersects deforestation events that were recorded for Years 3 and 4. When there have been more than two deforestation events, or deforestation events for the last two years, then the rectangle was assigned to High Risk (HR) stratum. All other rectangles were assigned to LR (Low Risk) stratum. After this, and based on geographical data provided by GFC, MR (Medium Risk) grid rectangles were selected from the LR stratum and stratified according to factors closely associated with risk of deforestation and forest degradation. In particular, data about the location of logging camps, mining dredges, settlements, and the existing road network were used (see Table 3.3 and Figure 3.1). This way, all grid rectangles that satisfied the following criteria were selected to be included in the MR stratum.

Contain at least one of: logging camps, mining dredges, or settlements,

<OR>

Intersect with at least one road.

Last but not least, we used the non-forest map of 1990 to identify rectangles that are almost completely deforested, and so no further deforestation event is expected within. When more than 90% of the rectangle contained non-forest in 1990, then this rectangle was assigned to 0R (Zero Risk) stratum. This resulted in the classification of grid rectangles into four strata: 435 HR, 794 MR, 1476 LR, and 132 0R. (see Figure 3-2 – left).

[4] According to the Interim Measures Report October 2013, the national boundary was defined by following information received from the GL&SC and with the aid of RapidEye imagery.

Table 3-3 Spatial data used to assist with defining risk strata

Data Group	Layer Name	Created/Update Frequency	Description
Admin	guyana_boundary	Received August 2013	Updated country boundary for Guyana.
Managed Forest Areas	logging_camps	N/A	Point location of logging camp sites, based on the Annual Operating plan.
Roads	gps roads_dd	3-6 months	All GPS roads and trails as at August 2013.
Mining Areas	mining_dredges	Upon granting of mining permit/licence/claim	Mining Dredge sites normally found in/around rivers
Population	Settlements	N/A	An extraction of a number of larger settlements from the place names point feature class.

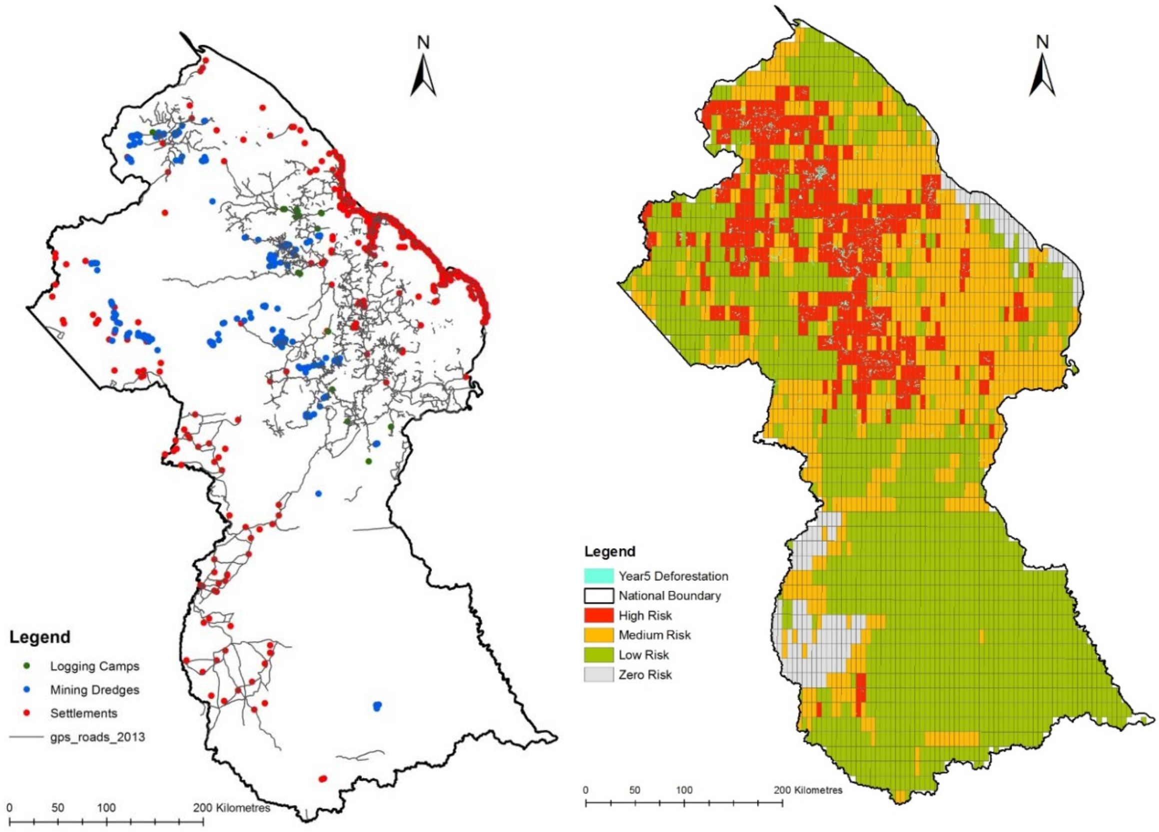


Figure 3-1 Criteria for sampling stratification (left). Strata with Y7 deforestation map (right).

The map in Figure 3-3 suggests that there is lower probability of sampling deforestation in the Low Risk stratum than the High and Medium Risk strata and so, in order not to under sample and miss deforestation events in this stratum, a weighting was applied when randomly selecting rectangles to analyse in detail. This resulted in 63 HR rectangles, 58 MR rectangles and 201 LR rectangles.

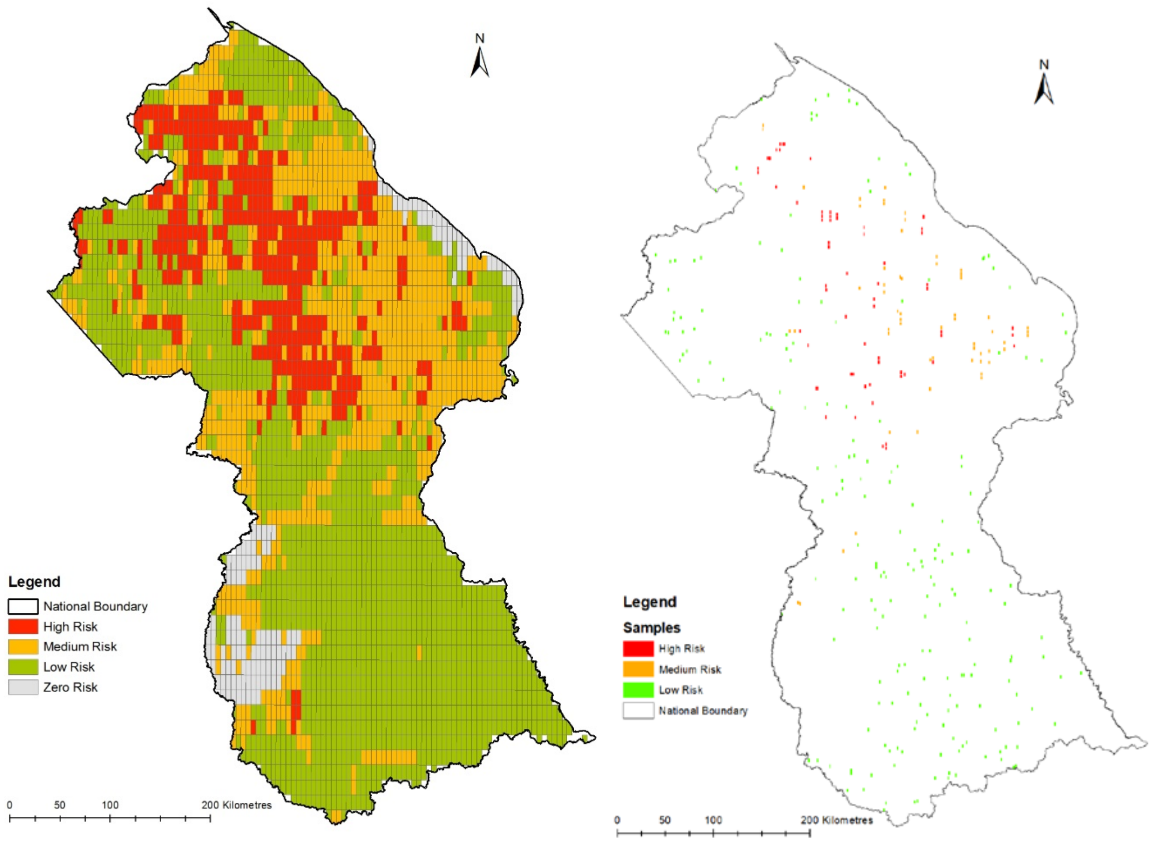


Figure 3-2 High, Medium, Low, and Zero Risk strata (left) and final random sampling of the strata (right image).

Within each first-stage sample, a systematic grid of 300 hectares was generated. The centre point of the each of the first-stage samples was generated randomly. In total 96,600 one-hectare samples became available for accuracy assessment.

For each primary sampling unit, the land cover class (e.g. Forest or Non-Forest, Degradation or Non-Degradation) is determined for the Year 7 deforestation and degradation map. The assessment follows a systematic procedure where the GIS table for the samples is populated using a bespoke GIS toolbar for accuracy assessment.

Specifically the tools used to interpret and validate Year 7 land cover change included high resolution satellite imagery (see Table 3-1). Also available were GIS data indicating mining, forestry and agricultural concessions.

Year 7 Change Assessment involved the collection of 322 equally-sized primary sample units (each with 300 ha) with a direct correspondence with Year 6. The reference data selected for the change assessment in Year 7 was a combination of PlanetScope, GeoVantage and Sentinel-2 imagery for the High and Medium Risk strata, and Sentinel-2 and Landsat imagery for the Low Risk stratum.

Figure 3-3 Historical deforestation data overlaid on sampling strata.

3.7 Precision of Area Estimates for Deforestation and Forest Degradation

The two-stage sampling with stratification of the primary units design optimises the probability of sampling deforestation and forest degradation in Year 7 when the area concerned represents only a small fraction of the national land area. Furthermore, there are several factors such as cloud cover, accessibility, safety and cost that limit the availability and quality of reference data.

A key consideration is minimising the risk of introducing any possible bias into the estimates. Bias may arise from sampling, from cloud cover patterns and perhaps from the distribution and coverage of the reference data. Sampling bias can be assessed from the joint probabliity matrices. The distribution of cloud cover has been assessed qualitatively from cloud cover masks but this can be quantified more formally from the sample area data and from the cloud mask data derived from analysis of the satellite imagery.

The validation team consists of six well qualified and experienced image interpreters, all of whom live in Guyana and work for the Guyana Forestry Commission. The analysis involved identifying change, paying strict attention of the definitions of 'forest cover', 'degraded forest cover' and 'non-forest' as well as the interpretation rules for deforestation and forest degradation.

Training was provided on two occasions in March/April 2018 and August 2018 to introduce the image interpretation team to the reference data sets, the ArcMap Change-Assessment Toolbar, and the mapping rules as detailed in the Standard Operating Procedures for Forest Change Assessment: A Guide for Remote Sensing Processing & GIS Mapping, along with Operating Procedures for REDD+ Accuracy Assessment.

3.8 Decision Tree for 2016-2017 (Year 7) Change Analysis

The analysis will report a gross deforestation change estimate based on a stratified random change estimator. This will provide confidence interval information on the deforestation estimate (i.e. the amount of change). Put another way, there is no sub-sampling other than to break down the measurement into a hectare-sized grid to make the assessment manageable. Appendix 8 in the Guyana REDD+ Monitoring Reporting & Verification System (2017) provides information about how decisions are made when a deforestation, forest degradation, or afforestation event is met by the interpreter, so as to fill up the information in a contingency matrix (see Table 3-4).

Table 3-3 Contigency matrix to represent change as detected by the assessment team.

	End Reference Class			
Start Reference Class	Forest	Degradation	NonForest	**Total**
Forest	Stable Forest	Loss	Loss	
Degradation	Gain	Stable Degradation	Loss	
NonForest	Gain	Gain	Stable NonForest	
Total				

When assessing degradation it is important to follow the Mapping Rules that define degraded-forest and non-forest that are detailed in the Standard Operating Procedure for Forest Change Assessment.

The most important points to note are:

1. Only areas of forest degradation that relate to Years 6 and 7 are assessed.
2. Areas of shifting cultivation are classified as “Pioneer” and “Rotational” even if they are smaller in size than the minimum mapping unit (1 ha). “Pioneer” areas are evaluated as deforestation and “Rotational” as forest degradation.
3. Areas of water bodies are classified as non-forest.
4. Areas cloud and shadow or missing data are labeled as *Omitted*.
5. Areas representing Year 8 change (post Dec 2017) were also omitted from the analysis as this change postdates the Year 7 reference imagery.

The rules for validating each sample unit point account for small discrepancies with the geometric alignment among the various remote sensing data sets. The change samples are ideally interpreted at 1:5,000 scale using 2016 imagery (PlanetScope or Sentinel-2) and 2017 imagery (GeoVantage, PlanetScope, or Sentinel-2) imagery. Minor discrepancies include a known some positional misalignments between PlanetScope and Sentinel-2 / GeoVantage aerial imagery. Other factors, other than human error, that might explain misinterpretation include land obscured by cloud or cloud shadow and change that is too small to be detected on the available cloud-free imagery. Furthermore, where a discrepancy between the mapping and the validation data is detected, an interpretation will be made of the correct assignment for the sample point. The toolbar included a confidence label on a 0-4 scale. The uncertainty refers to confidence in interpreting either change or the driver for change and is recorded on a four interval percentage scale. This allows for uncertainties in interpretation to be removed from the estimation and validation process if required.

4 RESULTS

4.1 GFC Change analysis

In preparation for the change assessment exercise, training sessions were run by Durham University in Guyana Forestry Commission (GFC) premises for the team of six GFC analysts in order to become familiar with the mapping / interpretation rules set out in the Standard Operating Procedure and to become familiar with the imagery, the GIS setup and the accuracy assessment toolbar. The training session was followed by consistency check on 900 samples, analysis of the disagreements and discussion among the team. A 'refresher' session also took place a week before the change assessment exercise began.

Following the training exercises, a second consistency check was performed after the change analysis was completed. The consistency analysis was conducted on 20 selected primary sample clusters where change was reported by any analyst in one or more of the 300 hectares in the sample. To be clear, the same 20 primary sample clusters were analysed by each interpreter and the results compared with Durham University's analysis. The results are summarised in Table 4-1.

Table 4-1 Consistency check results over 6000 samples, on the identification of change or no-change in the sample (grey cells) and the drivers of that change (white cells).

	User1	User2	User3	User4	User5	User6	DU
User1	Change	97.78%	97.65%	97.72%	96.90%	97.33%	98.11%
User2	91.63%		97.17%	97.27%	96.12%	97.32%	97.22%
User3	91.13%	91.43%		97.07%	95.80%	96.47%	97.85%
User4	89.48%	89.58%	87.92%		96.87%	96.70%	97.63%
User5	86.83%	86.90%	83.55%	85.32%		95.56%	96.57%
User6	90.58%	90.16%	89.07%	89.98%	83.86%		96.49%
DU	93.33%	90.57%	93.00%	87.83%	86.44%	87.51%	Drivers

The results in grey shading refer to the identification of change and the white cells relate to the drivers of change. The bottom row of the table shows the level of agreement for identifying change between each of the analysts and Durham University. Agreement on presence of change ranges from 86.4% to 93.3% with a mean agreement of 89.8%. The right hand column shows the level of agreement between each analyst and Durham University on assigning change drivers. These data show good levels of agreement with Durham University, ranging from 96.6% to 98.1% with a mean agreement of 97.3%.

While a mean level of agreement of 89.8% for identifying change / no-change appears high, it is of interest to identify the distribution of errors and these are shown as a contingency matrix in Table 4-2.

Table 4-2 Consistency check results over 6000 samples, showing the distribution of errors by type of change. F=Forest; NF=Non Forest; D=Degradation. DU=Durham University.

DU\Sum	F-NF	F-D	D-NF	F-F	D-D	NF-NF	D-F	NF-D	NF-F	DU-Agreement
F-NF	89	42	9	16	12	12	0	0	0	49.4%
F-D	42	207	5	140	42	32	0	0	0	44.2%
D-NF	8	7	18	9	12	18	0	0	0	25.0%
F-F	55	119	8	24186	282	616	24	13	6	95.6%
D-D	3	25	16	345	490	101	6	28	6	48.0%
NF-NF	31	24	34	635	384	3837	5	21	3	77.1%

The goal is to establish the level of agreement between the photointerpretation by the GFC analysts and Durham University (DU). A simple measure is to compute the percentage of cases where the GFC operators agree with DU (89.8%) but that statistic does not take into account any agreement that occurs by chance. An alternative is to test the hypothesis that the rows and the columns of the contingency matrix are independent using a Chi-squared or G-test (Congalton and Mead, 1983). Both tests show that the p-value is lower than the significance level alpha=0.05 and so the null hypothesis is rejected for the alternative hypothesis that there is a statistically significant link between the rows and the columns of the table.

Table 4-3 Test of independence between the rows and the columns

Wilks' G^2 (Observed value)	21505.220	Chi-square (Observed value)	42392.156
Wilks' G^2 (Critical value)	37.652	Chi-square (Critical value)	39.984
DF	25	DF	5
p-value	< 0.0001	p-value	< 0.0001
Alpha	0.05	Alpha	0.05

The strength of the relationship between the GFC interpreters and DU can be indicated from coefficients designed to measure association between binary variable such as Pearson's Phi (nominally -1 to +1 but maximum value determined by distribution of the variables), Contingency (ranges from -1 to +1) or Cohen's kappa (ranges from -1 to +1). Table 4-4 shows that all coefficients of association are positive but there is room for improvement.

Table 4-4 Association statistics for binary variables

Coefficient	Value
Pearson's Phi	1.153
Goodman & Kruskal Gamma	0.880
Contingency coefficient	0.755
Kendall's Tau	0.723
Cohen's kappa	0.722

It is evident that while there is strong agreement about whether a sample shows change (or not) but there is less agreement about the type of change. This is likely to occur for a number of possible reasons: random errors; sensor data used for interpretation; what contrast stretching each user used; care used with area measurement / estimation; and subjectivity over interpretation of rules in SOP (especially definitions of forest and degradation).

4.2 Change Sample Estimation

We treat the design as a stratified cluster design. The clusters are rectangles. The strata are HR, MR and LR. A simple random sample of rectangles from each stratum is taken. Then, within each rectangle, all hectares are systematically evaluated and all change measured quantitatively. This sample design is analysed primarily using PlanetScope and GeoVantage imagery supplemented by reinterpretation of Sentinel-2 satellite imagery in parts of Guyana that were within the Low Risk stratum, and occasionally Landsat where Sentinel-2 was obscured by clouds.

The reference data consisted of 96,600 primary sample units stratified into HR (18,900 ha), MR (17,400 ha) and LR (60,300 ha) areas as described in the sampling design (Section 3.6) and randomly sampled within each stratum. This design allows a probability-based inference approach to be applied. This approach assumes (1) that samples are selected from each stratum randomly; (2) that the probability of sample selection from each stratum can be estimated; (3) the sampling fraction in each stratum is close to proportional to the total population.

The total number of 1 ha samples analysed in the whole survey was 96,600. Of this total only 207 were omitted due to cloud cover or cloud shadow in the reference imagery. The proportion of the total omitted is 0.00214 which represents 0.2% of the sample. This is a significant improvement on Year 6 (2015-16) where the equivalent proportion of omitted samples was 0.05708 (5.7 %).

Key inputs to the analysis are the total number of samples in each stratum. These are 7,937,898 ha (21,580 sampled hectares) for HR, and 13,189,864 (33,539 sampled hectares) for LR. Apart from no change samples (Forest-Forest; Non Forest-Non Forest; Degradation-Degradation), the key changes are Forest-Non Forest, Forest-Forest Degradation, and Forest Degradation – Non Forest.

4.3 Software and estimators

To carry out the analysis, we have used the survey package available with the statistical package R Core Team (2014). This package is free and used by and supported by most of the world's academic statisticians, and increasingly is the commercial tool of choice. The survey package provided in Lumley (2004, 2014) provides functionality similar to that provided by the SAS package[5], and uses the same standard formulae for estimation of means and variances. These formulae are set out below and described conveniently in Lumley (2014).

Definitions and Notation

For a stratified clustered sample design, together with the sampling weights, the sample can be represented by an $n \times (P+1)$ matrix

$$(W, Y) = \left(w_{hij}, y_{hij}\right)$$

$$= (w_{hij}, y_{hij}^{(1)} y_{hij}^{(2)}, \dots \dots \dots, y_{hij}^{(p)})$$

Where

$h = 1{,}2, \dots \dots \dots, H$ is the stratum number, with a total of H strata

$i = 1{,}2, \dots \dots \dots, n_h$ is the cluster number within stratum h, with a total of n_h clusters

$j = 1{,}2, \dots \dots \dots, m_{hi}$ is the unit number within cluster i of stratum h, with a total of m_{hi} units

$p = 1{,}2, \dots \dots \dots, P$ is the analysis variable number, with a total of P variables

$n = \sum_{h=1}^{H} \sum_{i=1}^{n_h} m_{hi}$ is the total number of observations in the sample

[5] SAS SURVEYMEANS procedure. http://www.math.wpi.edu/saspdf/stat/pdfidx.htm

w_{hij} denotes the sampling weight for observation j in cluster i of stratum h

y_{hij} = $(y_{hij}^{(1)} y_{hij}^{(2)}, \dots \dots \dots, y_{hij}^{(p)})$ are the observed values of the analysis variables for observation j in cluster i of stratum h, including both the values of numerical variables and the values of indicator variables for levels of categorical variables.

Mean

$$\hat{\hat{Y}} = \frac{(\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij} y_{hij})}{w}$$

Where

$$w_{\dots} = \sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij}$$

Is the sum of the weights over all observations in the sample.

Confidence limit for the mean

The confidence limit is computed as

$$\hat{\hat{Y}} \pm StdErr\left(\hat{\hat{Y}}\right). t_{df,\infty/2}$$

Where $\hat{\hat{Y}}$ is the estimate of the mean, $StdErr\left(\hat{\hat{Y}}\right)$ is the standard error of the mean, and $t_{df,\infty/2}$is the $100(1 - {}^{\infty}/_{2})$ percentile of the t distribution with the dfcalculated as described in the section “t Test for the Mean”.

Proportions

The procedure estimates the proportion in level $c_k$for variable C as

$$\hat{p} = \frac{\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij} y_{hij}^{(q)}}{\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij}}$$

Where $y_{hij}^{(q)}$ is value of the indicator function for level $C = c_k$

$y_{hij}^{(q)}$equals $\mathbf{1}$ if the observed value of variables C equals c_k, and

$y_{hij}^{(q)}$ equals $\mathbf{0}$ otherwise.

Total

The estimate of the total weighted sum over the sample,

$$\hat{Y} = \sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij} y_{hij}$$

For a categorical variable level, $\hat{Y}$ estimates its total frequency in the population.

Variance and standard deviation of the total

$$\hat{V}(\hat{Y}) = \sum_{h=1}^{H} \frac{n_h(1-f_h)}{n_h-1} \sum_{i=1}^{n_h} (y_{hi\cdot} - \bar{y}_{h\cdots})^2$$

Where

$$y_{hi\cdot} = \sum_{j=1}^{m_{hi}} w_{hij} y_{hij}$$

$$\bar{y}_{h\cdot\cdot} = (\sum_{i=1}^{n_h} y_{hi\cdot}) / n_h$$

The standard deviation of the total equals

$$Std(\hat{Y}) = \sqrt{\hat{V}(\hat{Y})}$$

Confidence limits of a total

$$\hat{Y} \pm StdErr\left(\hat{Y}\right). t_{df,\infty/2}$$

4.4 Estimates of forest cover in Year 6

We can ignore that we have Year 7 information and obtain estimates of Year 6 forest cover. These can be compared to estimates obtained by other means. Table 4-5 shows the total areas classified as Degraded, Forest, and Non-Forest, together with a standard error and a 95% confidence interval. For example, the estimate of non-degraded Forest cover in 2016 (year 6) is 18,985,895 ha, standard error 22,920 ha, and 95% confidence interval (18,940,973; 19,030,816) ha.

Table 4-6 gives the same information as Table 4-5, but shows proportions rather than totals. So, the proportion of Forest cover in 2016 is 0.9020, standard error 0.0011, 95% confidence interval (0.8999, 0.9042). Note that proportions add to one.

Table 4-5 Analysis of Y6 hectares of all classes

	Hectares	SE	2.5%	97.5%
Y4 Degraded forest	156,122.70	6,472.56	143,436.70	168,808.70
Y4 Non degraded forest	18,985,894.50	22,919.72	18,940,972.70	19,030,816.30
Y4 Non forest	1,905,924.70	22,248.26	1,862,318.90	1,949,530.50

Table 4-6 Analysis of Y6 proportions of all classes

	Mean	SE	2.5%	97.5%
Y4 Degraded forest	0.0074	0.0003	0.0068	0.0080
Y4 Non-degraded forest	0.9020	0.0011	0.8999	0.9042
Y4 Non-forest	0.0906	0.0011	0.0885	0.0926

4.5 Estimates of forest cover in 2017 (year 7)

We now repeat these analyses for Year 7. Table 4-7 shows the total areas classified as degraded forest, non-degraded forest, and non-forest, together with a standard error and a 95% confidence interval. For example, the estimate of non-degraded forest cover in Year 7 is 17,602,715 hectares, standard error 23,307 hectares, and 95% confidence interval (17,557,033; 17,648,396) hectares. Table 4-8 shows proportions instead of totals. Otherwise the interpretation is as for Year 6.

Table 4-7 Analysis of Y6 hectares of all classes

	Hectares	SE	2.5%	97.5%
2017 Degraded forest	164,468.70	6,614.19	151,505.10	177,432.30
2017 Non-degraded forest	18,968,406.20	22,986.40	18,923,353.70	19,013,458.70
2017 Non forest	1,915,066.90	22,286.76	1,871,385.70	1,958,748.20

Table 4-8 Analysis of Y6 proportions of all classes

	Mean	SE	2.5%	97.5%
2017 Degraded forest	0.0078	0.0003	0.0072	0.0084
2017 Non-degraded forest	0.9012	0.0011	0.8991	0.9033
2017 Non forest	0.0910	0.0011	0.0889	0.0931

4.6 **Estimates of change from Year 6 to Year 7.**

We analyse change from Year 6 to Year 7 as follows. We have matched pairs of sample data, where the hectares seen in Year 6 are seen again in Year 7. Therefore it is natural to concentrate upon the change for each pair. This is analogous to the matched paired t-test, where we calculate differences between pairs, and then analyse the differences.

There are three possible outcomes for each pair, depending on how the hectare was classified in Year 6. If the classification had been Forest (non-degraded), the possibilities are Forest in Year 6 and Year 7, Forest in Year 6 and Degraded in Year 7, and Forest in Year 6 and Non Forest in Year 7. Therefore, these will result a total of nine possible combinations of change.

Table 4-9 Totals of Class Changes from Forest for 2016-2017

Stratum / Class	**Hectares**	**SE**	**2.50%**	**97.50%**
2016-2017 Forest.Degradation	4,764.3	730.4	3,332.5	6,196.3
2016-2017 Forest.NonForest	7,722.4	1,402.9	4,972.7	10,472.1
2016-2017 Forest.Forest	18,968,406.2	2,050.6	18,964,387.2	18,972,425.2

In Table 4-9 we estimate the area of Guyana which was classified as Forest in Year 6 and Non-Forest in Year 7. The estimate is 7,722 hectares, standard error 1,403 hectares, 95% confidence interval (4,972 ha; 10,472 ha). Appendix A gives the same information as Table 4-9, but disaggregated by stratum and by proportions rather than totals.

In Year 7 the GFC mapping team found no change from Non-Forest to Forest or Degraded Forest (reforestation). Note that it would be difficult to identify reforestation with any certainty in the LR stratum because only Sentinel-2 and Landsat data is available. Nevertheless, no reforestation was found in either the HR or MR strata using the high resolution PlanetScope or Sentinel-2 imagery.

The change from forest to degraded forest was measured precisely for each sample where change (forest loss) was identified. This was done manually using the 'measure tool' in ArcGIS and the value entered in the database using the Accuracy Toolbar to the nearest 5% for each sample hectare. The amount of loss is classed as degraded forest when forest area of 0.25 ha or more is lost, up to the point that 30% or less of the area is forest canopy covered; after that, the sample hectare would be classed as deforested. In this way partial deforestation and forest degradation is assessed quantitatively within each sample area. The total area for change from Forest to Degraded forest is 4,764 hectares, standard error 730 hectares, 95% confidence interval (3,332 ha; 6,196 ha), see table 4-9.

4.7 Estimating rate of change.

The key issue is to estimate the rate of change of gross deforestation. To do this, we restrict attention to hectares which in Year 6 were classified as forest or degraded, and then estimate the rates at which they continued to be Forest, or were classified as non-forest.

The estimated number of hectares of forest in Year 6 changed to Degraded Forest in Year 7 is 4,764 hectares with a standard error of 730 hectares, 95% confidence interval (3,332 ha; 6,196 ha). The estimated number of hectares of forest in Year 6 lost to non-forest in Year 7 is 7,722 hectares. These changes translate into a mean rate of deforestation on 0.051% with a SE of 0.0062% with a 95% confidence interval for the rate of change of 0.039% to 0.0630%, see Table 4-10.

Table 4-10 Mean deforestation rate per hectare (%)

	Mean	SE	2.5%	97.5%
Year 7 (2017) Forest loss	0.05085	0.00617	0.03876	0.06295

4.8 **Deforestation rate comparison**

Table 4-11 shows the Year 6 to Year 7 deforestation area and rate data compared. Note that the map-based estimate does not have a standard error associated with it but that the mapping and the change sample estimates are of similar magnitude. Note that the sample-based estimate considers only the areas available to sample, that is, the LR, MR and HR strata. We also defined a zero-risk stratum, with an area of 990,000 ha that is not included in calculation of the rate of change. This would account for the map-based estimate of change to be slightly different from the probability-based estimate, despite the map estimate showing a smaller amount of deforestation. The observed differences are within the sampling error.

Table 4-11 Comparison of Forest Change Estimates

	Forest area change (ha) Year 6- Year 7	Change Rate (%)	SE of Y7 Rate (%)
GFC / Indufor GIS Map Estimate	8,851	0.0480	
Durham Change Sample Estimate	7,722	0.0509	0.0062
Difference	-1,129	+0.0029	

4.9 **Drivers of change**

The primary driver of change in 2017 is mining which accounts for 82% of all deforestation and 81% of all forest degradation. A large area of burned forest was observed two primary sample areas which account for the relatively large estimate of 18% of the annual deforestation. Other areas of burning were associated with shifting agriculture practice close to Amerindian settlements which account for 11% of estimated degradation in 2017. Other minor drivers of forest degradation include forest loss around the margins of settlements (6%) and permanent agriculture (2%).

Table 4-12 Drivers of deforestation and forest degradation

Driver	Proportion for deforestation	Proportion for degradation
Agriculture		2%
Mining	82%	81%
Settlements		6%
Fire	18%	
Shifting agriculture		11%

All of the deforestation and forest degradation were identified in the High and Medium Risk strata and this includes the forest degradation associated with shifting cultivation. Figure 4-1 shows the distribution of loss plotted by change driver and Table 4-13 shows how the changes Figure 4-1 shows how the estimated degradation levels by driver maps onto the *Degradation Indicators* in the Guyana-Norway Agreement.

Figure 4-1 Change by Risk Stratum and driver

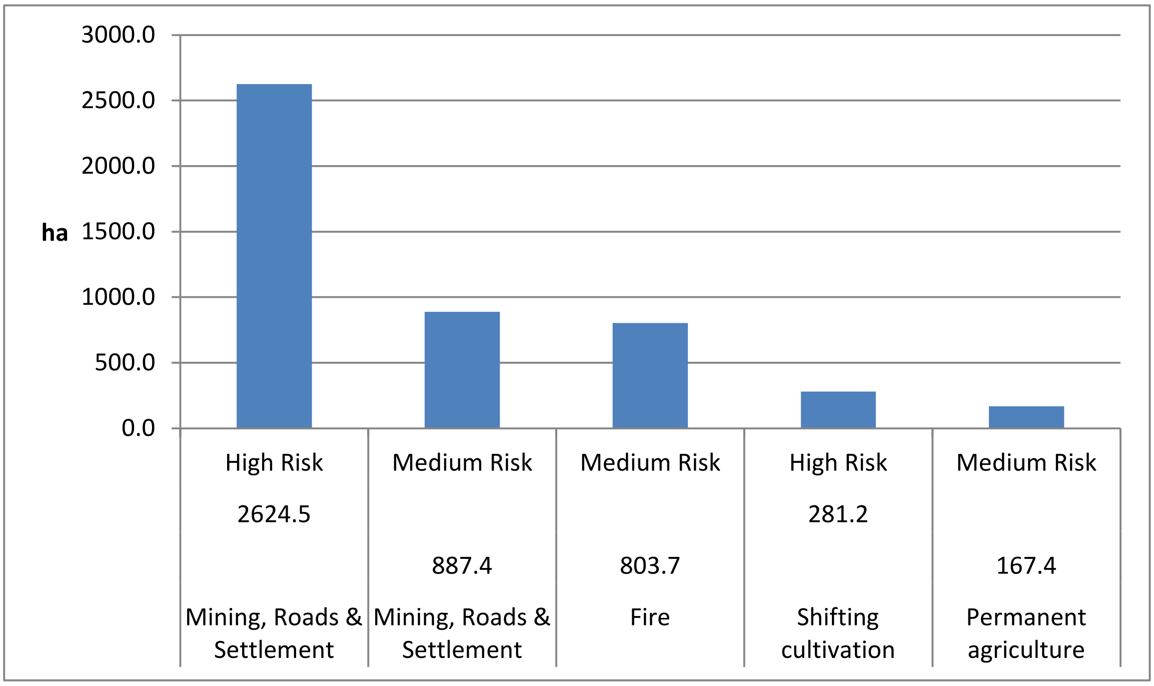


Table 4-13 Drivers of forest degradation by indicator

Drivers of degradation	Indicator	Unit	Adopted Reference Measure	Year 4 Period	Year 5 Period	Year 6 Period (Annualised)	Year 7 Period
Degradation Indicator	Determine the extent of degradation associated with new infrastructure such as mining, roads, settlements [7].	*ha/yr*	4 368	4 352	4 251	5,679	3,512
Emissions resulting from anthropogenic forest fires	Area of forest burnt each year should decrease.	*ha/yr*	1 706[1]	395	265	762	804
Emissions resulting from subsistence forestry, land use and shifting cultivation lands	Emissions resulting from communities to meet their local needs may increase as a result of inter alia a shorter fallow cycle or area expansion.	*ha/yr*	-	765	167	93	281
Natural / Unknown		*ha/yr*				802	0
Total		*ha*				7,336	4,764

[1] Degradation from forest fires is taken from an average over the past 20 years. This value is inclusive of all degradation drivers except for rotational shifting agriculture.

5 DISCUSSION

The results neatly divide into two areas that warrant further discussion:

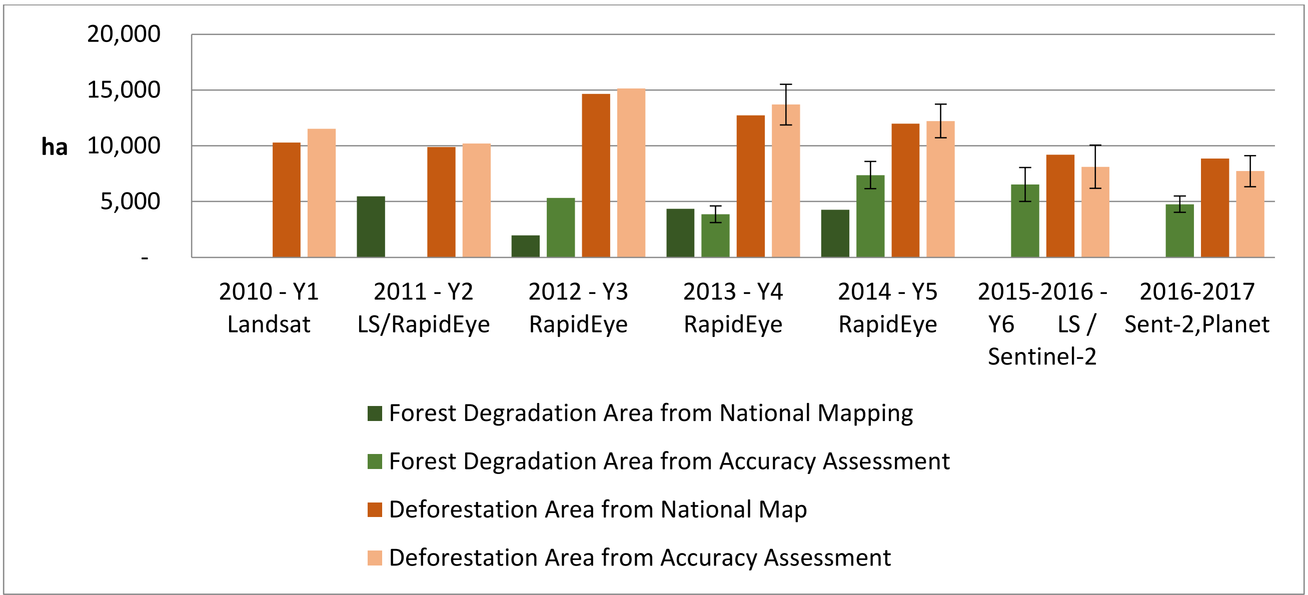
i) estimation of area and rate of deforestation and forest degradation using the change sample method;

ii) estimation of the drivers of forest loss and forest degradation.

5.1 Deforestation and Forest Degradation levels

The approach taken by GFC to produce a comprehensive (wall-to-wall) map for forest / non-forest for Guyana is ambitious and provides very precise, location-specific data. The mapped area of gross deforestation agrees well with the sample-based estimate giving confidence in the precision of the MRV mapping based primarily on Sentinel-2 MSI imagery. The accuracy assessment for deforestation did not check the map product, rather it estimated forest loss from an independent probability-based sample. The results suggest that (1) forest loss can be mapped to a good level of accuracy using Sentinel-2 and some Landsat 8 ALI data, and (2) that the level of forest loss estimated from the sample has a mean value close to 1,000 ha of the mapped value.

Figure 5-1 Deforestation and Forest degradation area of loss from Y1 to Y7



5.2 Drivers of Deforestation and Forest Degradation

The results from the stratified sample estimates confirms GFCs conclusion that mining and mining related infrastructure is the overwhelming driver for deforestation (82%).

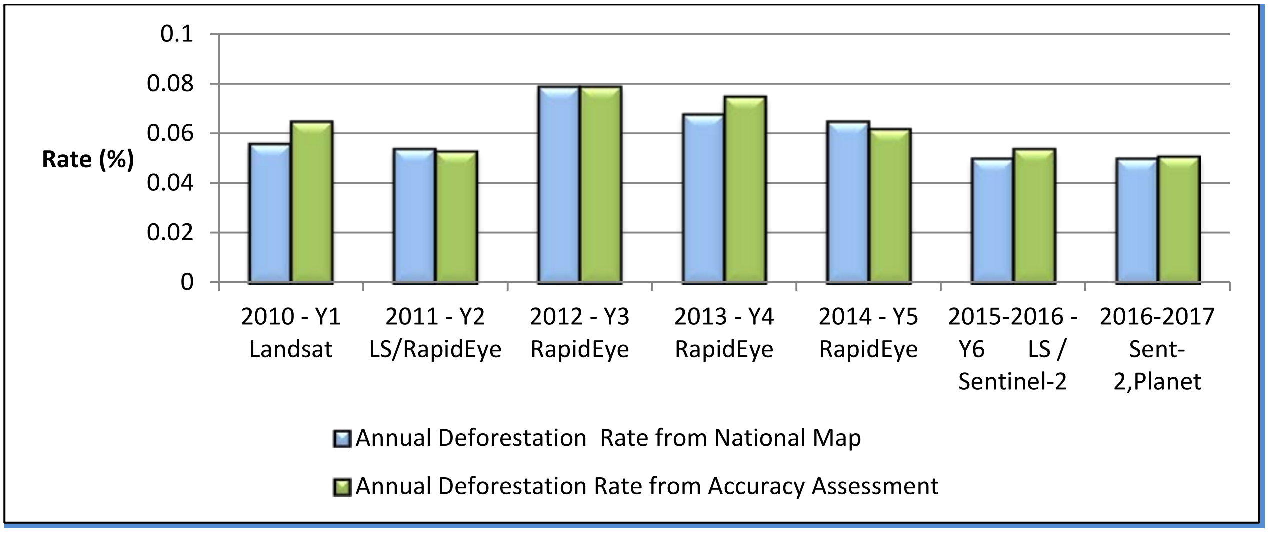
In the Years 2-5 degradation statistics were derived from wall-to-wall mapping by GFC using a combination of RapidEye 5m pixel size and Landsat 30 m pixel size imagery. In year 6 (2015-2016) RapidEye imagery was not available and so it was not possible to derive forest degradation maps from Landsat and some Sentinel-2 MSI data alone. Therefore, the level of forest degradation was estimated from the change sample reference data using interpretation of aerial imagery supplemented with PlanetScope and Sentinel-2 MSI data. The same approach was used for 2017 except the interpretation was carried out by the GFC Mapping Team rather than by the independent accuracy assessment team.

The results suggest that the GFC analysts have been able to identify areas of forest change consistently. Although the overall level of accuracy is high, there were many samples wrongly assigned to forest degradation rather than deforestation or no-change. Careful interpretation of the reference data, particularly using the aerial photography and the 3 m pixel size PlanetScope satellite images allowed allows forest degradation to be determined on a consistent basis.

Table 4-12 shows the deforestation and forest degradation data broken down by driver for the assessment sample. The data show that 82% of deforestation is associated with mining and mining infrastructure. It must be noted (i) that drivers of change are easier to identify on GeoVantage and PlanetScope imagery than on Sentinel-2 and (ii) that GeoVantage and PlanetScope was not available for the Low Risk stratum giving a possible bias in driver classification by stratum.

The breakdown of forest degradation by driver is also shown in Table 4-12 and this reveals that mining is also the dominant driver for forest degradation in Year 7. Using a change sample is clearly the most efficient and powerful way to detect change over a year. The levels of precision achieved are not likely to be much improved by taking a larger sample.

Figure 5-2 Deforestation Rate from Y1 to Y7



6 SUMMARY AND CONCLUSIONS

1. We conclude that the estimates of deforestation based on the mapping undertaken by GFC based largely on interpretation of Sentinel-2 MSI and PlanetScope imagery is of a good standard.
2. The methods used by GFC, and assisted by IAP, follow the good practice recommendations set out in the GOFC-GOLD guidelines and considerable effort has been made to acquire cloud free imagery towards the end of the census period October-December 2017 (Year 7).
3. The proportion of the total number of omitted samples is 0.00214 which represents 0.2% of the total sample. This is a significant improvement on Year 6 (2015-16) where the equivalent proportion of omitted samples was 0.05708 (5.7 %)
4. The estimate of the total area of change in the 12-month Year 7 period from forest to non-forest and degraded forest to non-forest is 7 722 ha, with a standard error of 1 403 ha and a 95% confidence interval (4 973 ha; 10 472 ha).
5. The estimate of the annual rate of deforestation that occurred over the Year 7 (12 month) period is 0.051% with a standard error of 0.0062% and a 95% confidence interval (0.0387%; 0.0630%).
6. The estimate the total area of change in the 12-month Year 7 period from forest to degraded forest between Y6 and Y7 is 4 764 ha, with a standard error of 730 ha and a 95% confidence interval (3 332 ha; 6 196 ha).
7. One change of 0.35 ha was detected within samples that fell within the boundary of the Intact Forest Landscape. The change was interpreted as forest degradation associated with shifting agriculture.
8. The GeoVantage (aerial survey) and PlanetScope data provided sufficient detail (spatial resolution) to assess the Sentinal-2 and PlanetScope deforestation mapping as provided by GFC. It would be difficult to make a precise assessment of degradation without access to high resolution imagery. Sentinel-2 MSI or Landsat ALI data are not sufficient for this purpose.

Recommendations

Based on the above conclusions, suggestions for SOP improvement could include:

1. To specify the order of imagery to be used for the interpretation (i.e. first use GeoVantage, then Planet, then Sentinel, and last Landsat).
2. To specify what contrast stretching to be done (or set default to the image extent, if possible).
3. To clarify the decision making process when the forest/non-forest area falls at or very near to the boundaries of the deforestation/degradation definitions.

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Appendix A: Statistical Tables

Table A1 – ANALYSIS OF 2016 Hectares OF ALL CLASSES

	Hectares	SE	2.50 %	97.50 %
2016 Degradation	156,122.70	6,472.56	143,436.70	168,808.70
2016 Forest	18,985,894.50	22,919.72	18,940,972.70	19,030,816.30
2016 NonForest	1,905,924.70	22,248.26	1,862,318.90	1,949,530.50

Table A2 - ANALYSIS OF 2016 Hectares OF ALL CLASSES BY STRATUM

	Hectares	SE	2.50 %	97.50 %
HR:2016 Degradation	70,134.1	3,447.5	63,377.0	76,891.1
LR:2016 Degradation	12,485.3	1,524.5	9,497.4	15,473.3
MR:2016 Degradation	73,503.2	5,261.6	63,190.7	83,815.8
HR:2016 Forest	3,011,436.6	6,453.0	2,998,789.0	3,024,084.2
LR:2016 Forest	10,595,773.4	9,897.2	10,576,375.2	10,615,171.5
MR:2016 Forest	5,378,684.6	19,639.7	5,340,191.4	5,417,177.7
HR:2016 NonForest	191,180.3	5,583.4	180,237.0	202,123.6
LR:2016 NonForest	540,596.9	9,790.6	521,407.6	559,786.1
MR:2016 NonForest	1,174,147.5	19,182.1	1,136,551.1	1,211,743.8

Table A3 - ANALYSIS OF 2016 Proportions OF ALL CLASSES

	Mean	SE	2.50%	97.50%
2016 Degradation	0.0074	0.0003	0.0068	0.0080
2016 Forest	0.9020	0.0011	0.8999	0.9042
2016 NonForest	0.0906	0.0011	0.0885	0.0926

Table A4 - ANALYSIS OF 2016 Proportions OF ALL CLASSES BY STRATUM

	Mean	SE	2.50%	97.50%
HR:2016 Degradation	0.0214	0.0011	0.0194	0.0235
LR:2016 Degradation	0.0011	0.0001	0.0009	0.0014
MR:2016 Degradation	0.0111	0.0008	0.0095	0.0126
HR:2016 Forest	0.9202	0.0020	0.9163	0.9240
LR:2016 Forest	0.9504	0.0009	0.9487	0.9521
MR:2016 Forest	0.8117	0.0030	0.8059	0.8175
HR:2016 NonForest	0.0584	0.0017	0.0551	0.0618
LR:2016 NonForest	0.0485	0.0009	0.0468	0.0502
MR:2016 NonForest	0.1772	0.0029	0.1715	0.1829

Table A5 - ANALYSIS OF 2017 Hectares OF ALL CLASSES

	Hectares	SE	2.50%	97.50%
2017 Degradation	164,468.70	6,614.19	151,505.10	177,432.30
2017 Forest	18,968,406.20	22,986.40	18,923,353.70	19,013,458.70
2017 NonForest	1,915,066.90	22,286.76	1,871,385.70	1,958,748.20

Table A6 - ANALYSIS OF 2017 Hectares OF ALL CLASSES BY STRATUM

Stratum / Class	Hectares	SE	2.50%	97.50%
HR:2017 Degradation	76,195.1	3,590.0	69,158.8	83,231.4
LR:2017 Degradation	12,485.3	1,524.5	9,497.4	15,473.3
MR:2017 Degradation	75,788.3	5,341.8	65,318.5	86,258.1
HR:2017 Forest	2,999,661.0	6,583.9	2,986,756.8	3,012,565.1
LR:2017 Forest	10,595,773.4	9,897.2	10,576,375.2	10,615,171.5
MR:2017 Forest	5,372,971.9	19,674.2	5,334,411.2	5,411,532.5
HR:2017 NonForest	196,895.0	5,661.0	185,799.6	207,990.3
LR:2017 NonForest	540,596.9	9,790.6	521,407.6	559,786.1
MR:2017 NonForest	1,177,575.1	19,204.1	1,139,935.8	1,215,214.4

Table A7 - ANALYSIS OF 2017 Proportions OF ALL CLASSES

	Mean	SE	2.50%	97.50%
2017 Degradation	0.0078	0.0003	0.0072	0.0084
2017 Forest	0.9012	0.0011	0.8991	0.9033
2017 NonForest	0.0910	0.0011	0.0889	0.0931

Table A8 - ANALYSIS OF 2017 Proportions OF ALL CLASSES BY STRATUM

Stratum / Class	Mean	SE	2.50%	97.50%
HR:2017 Degradation	0.0233	0.0011	0.0211	0.0254
LR:2017 Degradation	0.0011	0.0001	0.0009	0.0014
MR:2017 Degradation	0.0114	0.0008	0.0099	0.0130
HR:2017 Forest	0.9166	0.0020	0.9126	0.9205
LR:2017 Forest	0.9504	0.0009	0.9487	0.9521
MR:2017 Forest	0.8109	0.0030	0.8050	0.8167
HR:2017 NonForest	0.0602	0.0017	0.0568	0.0636
LR:2017 NonForest	0.0485	0.0009	0.0468	0.0502
MR:2017 NonForest	0.1777	0.0029	0.1720	0.1834

Table A9 - ANALYSIS OF 2016-2017 TOTALS OF CLASS CHANGES

	Hectares	SE	2.50 %	97.50 %
2016-2017 Degradation.Degradation	154,702.8	6,448.2	142,064.5	167,341.1
2016-2017 Forest.Degradation	9,765.9	1,497.3	6,831.3	12,700.5
2016-2017 Forest.Forest	18,968,406.2	22,986.4	18,923,353.7	19,013,458.7
2016-2017 Degradation.NonForest	1,419.9	570.0	302.6	2,537.1
2016-2017 Forest.NonForest	7,722.4	1,403.0	4,972.5	10,472.2
2016-2017 NonForest.NonForest	1,905,924.7	22,248.3	1,862,318.9	1,949,530.5

Table A10 - ANALYSIS OF 2016-2017 TOTALS OF CLASS CHANGES BY STRATUM

Stratum / Class	Hectares	SE	2.50%	97.50%
HR:2016-2017 Degradation.Degradation	69,095.1	3,422.5	62,387.2	75,803.0
LR:2016-2017 Degradation.Degradation	12,485.3	1,524.5	9,497.4	15,473.3
MR:2016-2017Degradation.Degradation	73,122.4	5,248.1	62,836.3	83,408.5
HR:2016-2017 Forest.Degradation	7,100.0	1,107.7	4,929.0	9,271.0
LR:2016-2017 Forest.Degradation	0.0	0.0	0.0	0.0
MR:2016-2017 Forest.Degradation	2,665.9	1,007.4	691.4	4,640.5
HR:2016-2017 Forest.Forest	2,999,661.0	6,583.9	2,986,756.8	3,012,565.1
LR:2016-2017 Forest.Forest	10,595,773.4	9,897.2	10,576,375.2	10,615,171.5
MR:2016-2017 Forest.Forest	5,372,971.9	19,674.2	5,334,411.2	5,411,532.5
HR:2016-2017 Degradation.NonForest	1,039.0	424.1	207.8	1,870.3
LR:2016-2017 Degradation.NonForest	0.0	0.0	0.0	0.0
MR:2016-2017 Degradation.NonForest	380.8	380.8	-365.6	1,127.3
HR:2016-2017 Forest.NonForest	4,675.6	899.2	2,913.2	6,438.0
LR:2016-2017 Forest.NonForest	0.0	0.0	0.0	0.0
MR:2016-2017 Forest.NonForest	3,046.8	1,077.0	935.9	5,157.6
HR:2016-2017 NonForest.NonForest	191,180.3	5,583.4	180,237.0	202,123.6
LR:2016-2017 NonForest.NonForest	540,596.9	9,790.6	521,407.6	559,786.1
MR:2016-2017 NonForest.NonForest	1,174,147.5	19,182.1	1,136,551.1	1,211,743.8

Table A11 - ANALYSIS OF 2016-2017 proportions OF CLASS CHANGES

	Mean	SE	2.5	%
2016-2017 Degradation.Degradation	0.00735	0.00031	0.00675	0.00795
2016-2017 Forest.Degradation	0.00046	0.00007	0.00032	0.00060
2016-2017 Forest.Forest	0.90120	0.00109	0.89906	0.90334
2016-2017 Degradation.NonForest	0.00007	0.00003	0.00001	0.00012
2016-2017 Forest.NonForest	0.00037	0.00007	0.00024	0.00050
2016-2017 NonForest.NonForest	0.09055	0.00106	0.08848	0.09262

Table A12 - ANALYSIS OF 2016-2017 proportions OF CLASS CHANGES BY STRATUM

Stratum / Class	Mean	SE	2.50%	97.50%
HR:2016-2017 Degradation.Degradation	0.02111	0.00105	0.01906	0.02316
LR:2016-2017 Degradation.Degradation	0.00112	0.00014	0.00085	0.00139
MR:2016-2017 Degradation.Degradation	0.01104	0.00079	0.00948	0.01259
HR:2016-2017 Forest.Degradation	0.00217	0.00034	0.00151	0.00283
LR:2016-2017 Forest.Degradation	0.00000	0.00000	0.00000	0.00000
MR:2016-2017 Forest.Degradation	0.00040	0.00015	0.00010	0.00070
HR:2016-2017 Forest.Forest	0.91656	0.00201	0.91261	0.92050
LR:2016-2017 Forest.Forest	0.95039	0.00089	0.94865	0.95213
MR:2016-2017 Forest.Forest	0.81085	0.00297	0.80503	0.81667
HR:2016-2017 Degradation.NonForest	0.00032	0.00013	0.00006	0.00057
LR:2016-2017 Degradation.NonForest	0.00000	0.00000	0.00000	0.00000
MR:2016-2017 Degradation.NonForest	0.00006	0.00006	-0.00006	0.00017
HR:2016-2017 Forest.NonForest	0.00143	0.00027	0.00089	0.00197
LR:2016-2017 Forest.NonForest	0.00000	0.00000	0.00000	0.00000
MR:2016-2017 Forest.NonForest	0.00046	0.00016	0.00014	0.00078
HR:2016-2017 NonForest.NonForest	0.05842	0.00171	0.05507	0.06176
LR:2016-2017 NonForest.NonForest	0.04849	0.00088	0.04677	0.05021
MR:2016-2017 NonForest.NonForest	0.17719	0.00289	0.17152	0.18287

Table A13 - ANALYSIS OF 2016-2017 TOTALS OF CLASS CHANGES FROM FOREST/DEGRADED

	Hectares	SE	2.50%	97.50%
2016-2017 Forest/Degraded.Degradation	164,468.7	6,614.2	151,505.1	177,432.3
2016-2017 Forest/Degraded.Forest	18,968,406.2	22,986.4	18,923,353.7	19,013,458.7
2016-2017 Forest/Degraded.NonForest	9,142.2	1,514.2	6,174.5	12,110.0
2016-2017 NonForest.NonForest	1,905,924.7	22,248.3	1,862,318.9	1,949,530.5

Table A14 - ANALYSIS OF 2016-2017 TOTALS OF CLASS CHANGES BY STRATUM FROM FOREST/DEGRADED

Stratum / Class	Hectares	SE	2.50%	97.50%
HR:2016-2017 Forest/Degraded.Degradation	76,195.1	3,590.0	69,158.8	83,231.4
LR:2016-2017 Forest/Degraded.Degradation	12,485.3	1,524.5	9,497.4	15,473.3
MR:2016-2017 Forest/Degraded.Degradation	75,788.3	5,341.8	65,318.5	86,258.1
HR:2016-2017 Forest/Degraded.Forest	2,999,661.0	6,583.9	2,986,756.8	3,012,565.1
LR:2016-2017 Forest/Degraded.Forest	10,595,773.4	9,897.2	10,576,375.2	10,615,171.5
MR:2016-2017 Forest/Degraded.Forest	5,372,971.9	19,674.2	5,334,411.2	5,411,532.5
HR:2016-2017 Forest/Degraded.NonForest	5,714.6	993.9	3,766.5	7,662.7
LR:2016-2017 Forest/Degraded.NonForest	0.0	0.0	0.0	0.0
MR:2016-2017 Forest/Degraded.NonForest	3,427.6	1,142.3	1,188.8	5,666.4
HR:2016-2017 NonForest.NonForest	191,180.3	5,583.4	180,237.0	202,123.6
LR:2016-2017 NonForest.NonForest	540,596.9	9,790.6	521,407.6	559,786.1
MR:2016-2017 NonForest.NonForest	1,174,147.5	19,182.1	1,136,551.1	1,211,743.8

Table A15 - ANALYSIS OF 2016-2017 proportions OF CLASS CHANGES FROM FOREST/DEGRADED

Class	Mean	SE	2.50 %	97.50 %
2016-2017 Forest/Degraded.Degradation	0.00781	0.00031	0.00720	0.00843
2016-2017 Forest/Degraded.Forest	0.90120	0.00109	0.89906	0.90334
2016-2017 Forest/Degraded.NonForest	0.00043	0.00007	0.00029	0.00058
2016-2017 NonForest.NonForest	0.09055	0.00106	0.08848	0.09262

Table A16 - ANALYSIS OF 2016-2017 proportions OF CLASS CHANGES BY STRATUM FROM FOREST/DEGRADED

Stratum / Class	Mean	SE	2.50%	97.50%
HR:2016-2017 Forest/Degraded.Degradation	0.02328	0.00110	0.02113	0.02543
LR:2016-2017 Forest/Degraded.Degradation	0.00112	0.00014	0.00085	0.00139
MR:2016-2017 Forest/Degraded.Degradation	0.01144	0.00081	0.00986	0.01302
HR:2016-2017 Forest/Degraded.Forest	0.91656	0.00201	0.91261	0.92050
LR:2016-2017 Forest/Degraded.Forest	0.95039	0.00089	0.94865	0.95213
MR:2016-2017 Forest/Degraded.Forest	0.81085	0.00297	0.80503	0.81667
HR:2016-2017 Forest/Degraded.NonForest	0.00175	0.00030	0.00115	0.00234
LR:2016-2017 Forest/Degraded.NonForest	0.00000	0.00000	0.00000	0.00000
MR:2016-2017 Forest/Degraded.NonForest	0.00052	0.00017	0.00018	0.00086
HR:2016-2017 NonForest.NonForest	0.05842	0.00171	0.05507	0.06176
LR:2016-2017 NonForest.NonForest	0.04849	0.00088	0.04677	0.05021
MR:2016-2017 NonForest.NonForest	0.17719	0.00289	0.17152	0.18287

Table A17 - ANALYSIS OF 2016-2017 TOTALS OF CLASS CHANGES FROM FOREST

Stratum / Class	Hectares	SE	2.50%	97.50%
2016-2017 Forest.Degradation	4,764.3	730.4	3,332.5	6,196.3
2016-2017 Forest.Forest	18,968,406.2	2,050.6	18,964,387.2	18,972,425.2
2016-2017 Forest.NonForest	7,722.4	1,402.9	4,972.7	10,472.1