



Using the regression estimator with Landsat data to estimate proportion forest cover and net proportion deforestation in Gabon



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ABSTRACT

Forest cover maps were produced for the Gabonese Agency for Space Studies and Observations (AGEOS) for 1990, 2000 and 2010 for an area of approximately 102,000 km² corresponding to 38% of the total area of Gabon and representative of the range of human pressure on forest resources. The maps were constructed using a combination of a semi-automated classification procedure and manual enhancements to ensure the greatest possible accuracy. A two-stage area frame sampling approach was adopted to collect reference data for assessing the accuracy of the forest cover maps and to estimate proportion forest cover and net proportion deforestation. A total of 251 2 × 2 km segments or primary sample units (PSUs) were visually interpreted by a team of photo-interpreters independently from the map production team to produce a reference dataset representing about 1% of the study area. Paired observations were extracted from the forest cover map and the reference data for a random selection of 50 secondary sample units (SSUs) in the form of pixels within each PSU. Overall map accuracies were greater than 95%. PSU and SSU outputs were used to estimate proportion forest cover and net proportion deforestation using both direct expansion and model-assisted regression (MAR) estimators. All proportion forest cover estimates were similar, but the variances of the MAR estimates were smaller than variances for the direct expansion estimates by factors as great as 50. In addition, SSU-level estimates had standard errors slightly greater than those of PSU-level estimates, but the differences were small, particularly when auxiliary variables were obtained from forest cover maps. Therefore, a two-stage sampling approach was justified for collecting a reliable forest cover reference dataset for estimating proportion forest cover area and net proportion deforestation. Finally, despite large overall map accuracies, net proportion deforestation estimates obtained from the maps alone can be misleading as indicated by the finding that the MAR estimates, which included adjustment for bias estimates, were twice the non-adjusted map estimates for the periods 1990–2000 and 1990–2010. The results confirmed the expected generally small level of net deforestation for Gabon. However, loss of forest cover appears to have almost stopped in the last 10 years. One explanation could be the creation of national parks and the implementation of forest concession management plans from 2000 onward, but this should be further explored.

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1. Introduction

1.1. Forest cover monitoring in central Africa

The role of tropical forests as the largest reservoir of biodiversity and as a major carbon sink is well-recognized. The Central African forest is the second largest tropical forest area after the Amazon, but it is still relatively well-preserved, making its conservation and management all the more crucial (de Wasseige et al., 2012; Justice, Wilkie, Zhang, Brunner, & Donoghue, 2001). Although uncertainties are large (Achard et al., 2002), tropical deforestation and forest degradation are estimated to contribute approximately 20% of all greenhouse gas (GHG) emissions

(Achard et al., 2007; Gullison et al., 2007). Therefore, reducing tropical deforestation and degradation can have a direct impact on the reduction of GHG emissions.

Consequently, the post-Kyoto protocol mechanism, Reduction of Emissions from Deforestation and forest Degradation (REDD), was proposed and initiated at the UNFCCC Conference of Parties (COP) 11 in Montréal in 2005. GHG inventories as part of the UNFCCC process require two inputs: activity data and emissions factors (IPCC, 2006). In the REDD context, activity data refer to the extent of forest cover and forest cover change and require spatially explicit estimates (GOFCC-GOLD, 2011). Emissions factors refer to quantities of GHG emissions per unit area for an activity and rely primarily on field inventory data for estimation. Thus, monitoring of forest cover and forest cover change by means of a robust and transparent national forest monitoring system is a pre-requisite for a national REDD policy. The Gabonese Agency for

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Space Studies and Observations (AGEOS) was established in 2010 with the aims of implementing a national infrastructure for environmental monitoring and mitigating the impacts of climate change. In addition, the AGEOS objectives included building the capacity to monitor forest cover at the national level.

Although national forest monitoring systems could rely solely on information acquired by ground sampling, the budgetary and logistical constraints associated with intensive sampling of remote and inaccessible forests make this option infeasible for many tropical countries. For these countries, maps in the form of classifications of multi-spectral satellite imagery are routinely recommended as another source of information for forest cover and forest cover change. However, a crucial difference between ground sample observations and maps based on classified imagery must be noted. Whereas ground sample observations are assumed to be observations without error, apart from minimal measurement error, maps based on satellite image classifications are predictions and include varying degrees of inherent uncertainty. Thus, complete reliance on image-based estimates of forest cover and forest cover change entails considerable risk if no compensation is made for bias resulting from systematic classification errors. In particular, satellite imagery should not be used apart from a sample of reference data for purposes of estimating both bias and uncertainty.

Duveiller, Defourny, Desclée, and Mayaux (2008) and Ernst et al. (2013) used approaches based on a systematic sampling of classified satellite image extracts to estimate regional and country-level net deforestation for Central Africa. However, both studies emphasized that estimates for three of six countries, including Gabon, were less reliable due to the lack of sufficient cloud-free imagery. Obviously, augmentation of ground sampling with wall-to-wall mapping is more expensive than simply ground sampling. Nevertheless, wall-to-wall land cover maps fulfill several functions when monitoring forest cover change: (1) they can be used to augment ground data and thereby enhance estimates based solely on ground sample data; (2) they can serve as a reference baseline against which future change can be assessed; and (3) they can be used to assess the impact of forest management policies and for legal enforcement. For an appropriate interpretation of results, Achard et al. (2007) emphasized the need for a consistent methodology and spatial resolution. Wall-to-wall mapping was also applied to the Congo basin region by Hansen et al. (2008), and although country-level forest cover estimates were based on 250×250 -m resolution MODIS data, forest cover change estimates based on the combination of MODIS and Landsat were only reported for three broad landscape areas. These examples highlight the need to adopt a national-level approach to ensure that country specific situations are accommodated.

Gabon is recognized as one of the cloudiest areas of the Congo basin and in Africa more generally. Therefore, a specific approach is required to produce country level estimates of forest cover and forest cover change. Hansen et al. (2008) addressed the issue of persistent cloud cover in the Congo Basin region by combining fine and medium spatial resolution imagery despite the potential loss of spatial detail. Zhu, Woodcock, and Olofsson (2012) suggested using the entire Landsat archive available for a given area to monitor forest disturbance on a continuous basis, although such an application has only become possible since the Landsat archive has been made freely available.

Central Africa is also one of the few blind spots in terms of Earth Observation (EO) data acquisition because no satellite receiving station covers the area. Thus, when the Landsat 4 TM instrument failed in the early 1990s and Landsat 5 lost its transmission via a Geostationary satellite in 1992 (Loveland & Dwyer, 2012), only direct reception remained possible. Unfortunately, no Landsat 5 acquisition was possible over most of Central Africa until the launch of Landsat 7 in 1999. In addition, Landsat data distribution was relinquished to a commercial company in the mid-1980s, causing further disruption in the consolidation of the global Landsat archive (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012). Despite these difficulties, Landsat data still provide

the best EO data coverage of the country since the late 1980s, because few other sensors have been available over such a long period. Little SPOT imagery was acquired until recently, and IRS data are rarely acquired for Africa. Due to the complexity of its use and lack of availability for Gabon, SAR data is recommended only for gap filling by the REDD Source Book (GOF-C-GOLD, 2011).

Multiple reports of forest cover and cover change area estimates at regional or global levels have been published (Achard et al., 2002; Duveiller et al., 2008; Ernst et al., 2013), but estimates are either not available at the country level or the authors themselves acknowledge that the data are less reliable for some countries. In addition, the IPCC (2006) specifically notes that good practice requires that estimates should be accompanied by measures of uncertainty. Error or confusion matrices (Congalton, 1991) and their associated measures of accuracies (Stehman, 1997) are starting points for assessing uncertainty. However, the measures of accuracy estimated from confusion matrices do not directly provide uncertainty measures in the form of confidence intervals as are required to assess the significance of the changes in estimates of forest cover (McRoberts, 2011). An approach based on a statistical, model-assisted, regression estimator that satisfies this requirement was developed in the 1970s and 1980s for crop statistics (Allen, 1990; Carfagna & Gallego, 2005; Gallego, 2004; Taylor, Sannier, Delincé, & Gallego, 1997) and was successfully applied to estimating forest cover over a small study area in Southern Brazil by Deppe (1998). A similar approach using satellite data was used by McRoberts and Walters (2012) and McRoberts (2014) to estimate net deforestation in the United States of America and by Vibrans, McRoberts, Moser, and Nicoletti (2013) to estimate forest cover in Brazil.

1.2. Aim and objectives

The aim of this study was to develop and illustrate statistically rigorous methods for estimating proportion forest cover and net proportion deforestation that are suitable for use in tropical countries such as Gabon. For purposes of demonstrating applicability at a national scale, a large study area was selected (Section 2), and the relevant reference years of 1990, 2000, and 2010 were selected. A secondary objective was to determine the relative merits of a two-stage sampling design that would potentially require less effort to implement, compared with a one-stage sampling design, for a pre-operational forest cover monitoring system in Gabon with potential for application in other tropical high forest cover countries.

The study makes no attempt to identify the type of forest cover change (GOF-C-GOLD, 2011), but focuses on estimating proportion forest cover and net proportion deforestation where net deforestation is the net result of gross deforestation, afforestation, and reforestation and is assumed to be attributed solely to human activity. The technical approach combined sample-based data collection and wall-to-wall mapping using a regression estimator to estimate proportion forest cover, net proportion deforestation, and their uncertainties. One-stage and two-stage estimators were used to assess the contributions of the wall-to-wall, image-based maps with respect to increasing accuracy and precision and with respect to the ease of data collection.

2. Data

2.1. Study area

Gabon is an equatorial country located in the Congo basin region of Central Africa with a total area, including land and water, of 267,667 km² (CIA, 2009). A small population and substantial oil and mineral resources contribute to making Gabon one of the wealthiest countries in Africa. One consequence is that equatorial forest cover in Gabon is among the greatest in the world, and most of it has been preserved. Gabon's location on the Equator and on the Atlantic Ocean

coast explains why it is one of the cloudiest regions in Africa, a feature that makes monitoring using optical satellite imagery particularly challenging.

A sufficiently large study area was selected to demonstrate the applicability of the methodology for national coverage and to represent the country's anthropogenic pressure on forest resources. Although complete Landsat coverage for Gabon requires all or parts of 19 scenes (Fig. 1), six scenes representing a total area of 102,463 km² and 38% of the country area were deemed sufficient for the purposes of this study. The study area ranges geographically from the main metropolitan area of the country's capital city, Libreville, with high expected anthropogenic pressure to the remote Minkébé National Park in the northeast corner of the country where little deforestation is expected.

Gabon has yet to adopt a national definition of forest. However, the UNFCCC (2006) defines forest as “a minimum area of land of 0.05–1.0 hectare (ha) with tree crown cover (or equivalent stocking level)

of more than 10–30 per cent with trees with the potential to reach a minimum height of 2–5 meters at maturity in situ.” For this study, the largest values in the ranges were selected for defining forest land: minimum area of 1 ha, tree crown cover of at least 30%, and minimum potential height at maturity of 5 m.

2.2. Remotely sensed data

Although the study area was defined by the boundaries of six Landsat World Reference System 2 (WRS) path/row combinations, multiple Landsat images for each scene were required to obtain sufficient cloud free coverage for the three selected reference years. In addition 13 ASTER scenes were used for 2010 as additional auxiliary data to support the Landsat image classification.

The majority of Landsat imagery acquired for this study was processed for standard terrain correction Level 1 T. Landsat L1T data

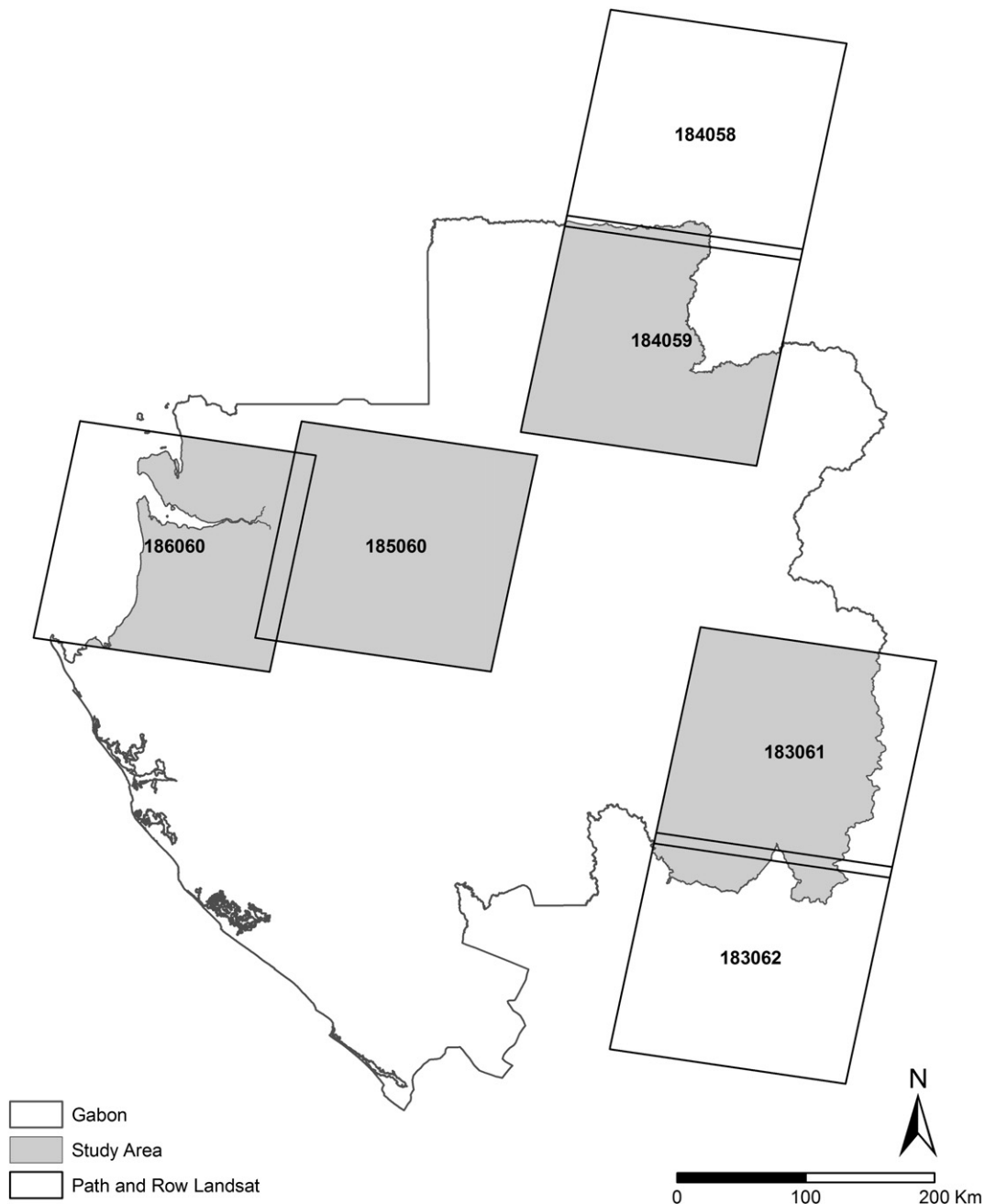


Fig. 1. Location of study area within Gabon and identification of Landsat data coverage.

are georeferenced to UTM projection (WGS84 Datum). The image-to-image registration is performed using Landsat Global Land Survey (GLS) 2000 as reference dataset (Gutman et al., 2008). All Landsat 7 ETM+ and Landsat TM-5 data were visually inspected to check the overall quality and a minimum set of 10 systematically distributed check points were selected to assess the quality of the registration using GLS-2000 as a reference. In cases when the root mean square error exceeded 30 m or the data acquired were not Level 1 T processed, the image registration was adjusted using a first-order polynomial model and resampled to an output pixel size of 30-m $\times$ 30-m to create a consistent dataset for change detection. A topographic normalization was applied to every image using a Lambertian reflectance model (Colby, 1991) using the Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model.

A simple interactive cloud and cloud shadow detection algorithm was applied to every image based on the combination of an unsupervised classification approach (ISODATA) and a visual comparison of the results with the input image to determine the threshold between cloud, cloud shadow and non-cloudy pixels. A cloud mask was produced for each input image to estimate cloud cover statistics and to determine the effective coverage of each image for the three reference years. This approach was preferred to a more complex cloud detection algorithm (Hagolle, Huc, Pascual, & Dedieu, 2010; Irish, Barker, Goward, & Arvidson, 2006; Zhu & Woodcock, 2012) because it was deemed more robust after initial testing. An example of the cloud mask is shown in Fig. 2.

For reference data collection, the Landsat imagery was used in combination with available online image and map archives including Bing Maps, Google Earth, Google Maps and Open Street Map. In addition, very fine resolution satellite imagery and detailed general purpose map data were used for some locations.

3. Methods

3.1. Sample design

In the absence of a national forest inventory or other suitable reference dataset, an area frame sampling approach was adopted to estimate forest cover area with the option of using forest cover maps as sources of auxiliary data. The main benefits of using such an approach are twofold: (i) it can be used independently from the forest cover map to produce forest cover area estimates at the national level using the direct expansion method, and (ii) it provides a means to collect reliable reference data for map accuracy assessment.

A probability sampling design is preferable because of its objectivity. Simple random, stratified random, clustered random and systematic designs are all examples of probability sampling designs (Stehman & Czaplewski, 1998). The main drawback of simple random designs is that some portions of the population may not be adequately sampled. Stratified approaches overcome this drawback, but they usually require a physical basis for stratification such as maximum elevation or broad land use types. Such information was either not relevant for Gabon or was not known because little a priori knowledge of the nature of forest cover dynamics for the entire country was available. Systematic approaches also overcome geographic distribution problems, but can pose problems if the landscape features cyclical patterns. Cluster sampling is often used to reduce the costs of the collection of reference data, but does not resolve geographic distribution problems.

Another method that improves the geographic distribution of a sample entails dividing the study area into blocks and then randomly selecting primary sampling units (PSU) within each block where a PSU is defined as an area smaller than a block. A two-stage sampling approach is implemented by further selecting secondary sampling units (SSU) within PSUs in the second-stage. The advantage of this approach is that data collection costs can be reduced, but a disadvantage is that the variance is increased because of the uncertainty of within-

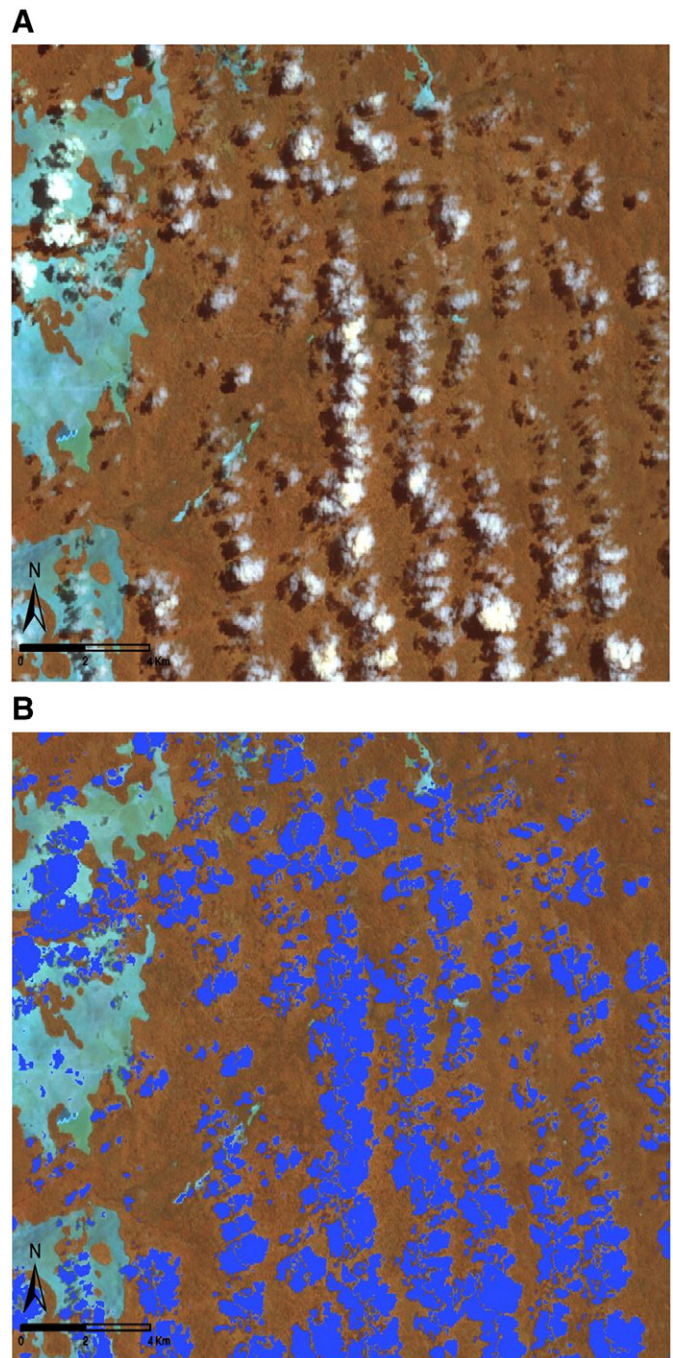


Fig. 2. Illustration of the cloud and cloud shadow mask product.

PSU estimates. Two-stage sampling is considered suitable for accuracy assessment of land cover maps (Stehman, 2009) and was adopted for this study because it represented the best compromise between the ease of data collection and a good geographic distribution. No fixed rules guide the selection of the size of PSUs other than to find a compromise between the overall number of observations and a reasonable level of uncertainty for within-PSU estimates. The respective sizes of PSUs and blocks are adjusted to correspond to the desired sampling intensity.

For this study, the population consisted of a finite number of mutually exclusive units in the form of 30-m $\times$ 30-m Landsat pixels. The population was partitioned into 251 blocks, each of size 20-km $\times$ 20-km, for purposes of facilitating systematic sampling to achieve uniform spatial coverage. Each block was further divided into PSUs in the form of 2-km $\times$ 2-km segments whose size was selected after initial

trials that considered the complexity and fragmentation of the landscape (Fig. 3). A first-stage sample was constructed by randomly selecting one segment with assumed equal positive probability from each block where $S_i = \{i: i = 1, \dots, n\}$ indexes the selected segments. Within each segment, the 30-m $\times$ 30-m Landsat pixels served as SSUs. For each $i \in S_i$, a second stage sample was constructed by randomly selecting 50 pixels with assumed equal positive probability where $S_i = \{j: j = 1, \dots, m\}$ indexes the selected pixels. Because the segments were not selected to correspond to a fixed number of pixels, segment boundaries did not correspond exactly to pixel boundaries. Thus, some pixels straddled segment boundaries with three immediate results: (i) the possible number of pixels per segment varied slightly from 4577 to 4710, (ii) the probabilities of inclusion into the second stage sample for boundary pixels were less than for interior pixels, and (iii) the same boundary pixel could be selected for samples in each of two adjacent segments. For estimation purposes, the mean number of pixels per segment, 4644, was used for the analyses. In addition, the effects of unequal probabilities of inclusion were ignored because the proportion of the total number of pixels in a segment represented by boundary pixels was only approximately 0.05 and because the probability that adjacent segments would be selected in the first-stage sample was judged to be negligible.

3.2. Reference data collection

Collection of reference data in the field was not feasible in Gabon because of the large mapped area, the difficulty of access in dense humid forest, and the lack of time and budget. Stehman (2009) asserted that “ground truth” is rarely available and that accuracy assessment is often made relative to some “higher quality determination of land cover”. Czaplewski (2003) indicated that visual interpretation is acceptable if the resolution of EO data is sufficient compared to the thematic classification system. For this study, a forest expert working independently of the map production team used the available Landsat imagery, other available sources of imagery and auxiliary data to interpret each pixel within sampled segments with respect to forest/non-forest. Pixel-level reference data consisted of the forest/non-forest interpretations, and segment-level reference data consisted of the proportions of pixels interpreted as forest. The final output is a set of polygonal, vector-based segments and a dataset consisting of pixel-level observations for each segment for

each of the reference years 1990, 2000 and 2010. The same segments and pixels were used for all three reference years.

The advantage of interpreting a sample of pixels rather than all pixels in a segment is less cost; the disadvantage is that the variance of the overall estimate increases because the pixel-based estimates of proportion forest for each segment have uncertainties. The difference in precision can be assessed by comparing the variance of the overall estimate obtained using the segment-level proportions of forest interpretations with a one-stage estimator and the variance obtained using the pixel-level forest/non-forest interpretations with a two-stage estimator.

3.3. Thematic classification

The study area was divided into four production units based on the Landsat WRS2 Path/row (186/060, 185/060, 184/058 & 059 and 183/061 & 062 as shown in Fig. 1). Landsat scene selection as input to the classification process was based on acquisition date and the useable proportion of the image (free of clouds, cloud shadows and gaps for Landsat 7 SLC off). The image whose date was closest to the reference year was used first, other images were added based on their acquisition dates, and image selection was stopped when 100% or nearly 100% coverage of the production unit was achieved. As a rule, images were selected within a three-year time period before and after the reference year, although for the 1990 reference year image data from 1984 were necessary for a very small portion of the area.

Each image was classified separately using an unsupervised classification approach based on the ISODATA algorithm for 20–40 spectral classes, depending on the image used, to ensure good representation of the thematic classes' variability. The spectral classes were regrouped into forest and non-forest thematic classes. When all the images for a production unit were processed, the results were aggregated into a single forest/non-forest raster layer based on the image selection rule described above. A post-processing classification routine was applied to vectorize the results and eliminate polygons smaller than 1 ha for purposes of consistency with the adopted forest definition (Section 2.1). The classification process and outputs are illustrated in Fig. 4.

The 1990 and 2010 forest cover maps were produced by stratifying the 1990 and 2010 images according to the forest and non-forest strata obtained from the 2000 forest cover map. Each stratum was classified

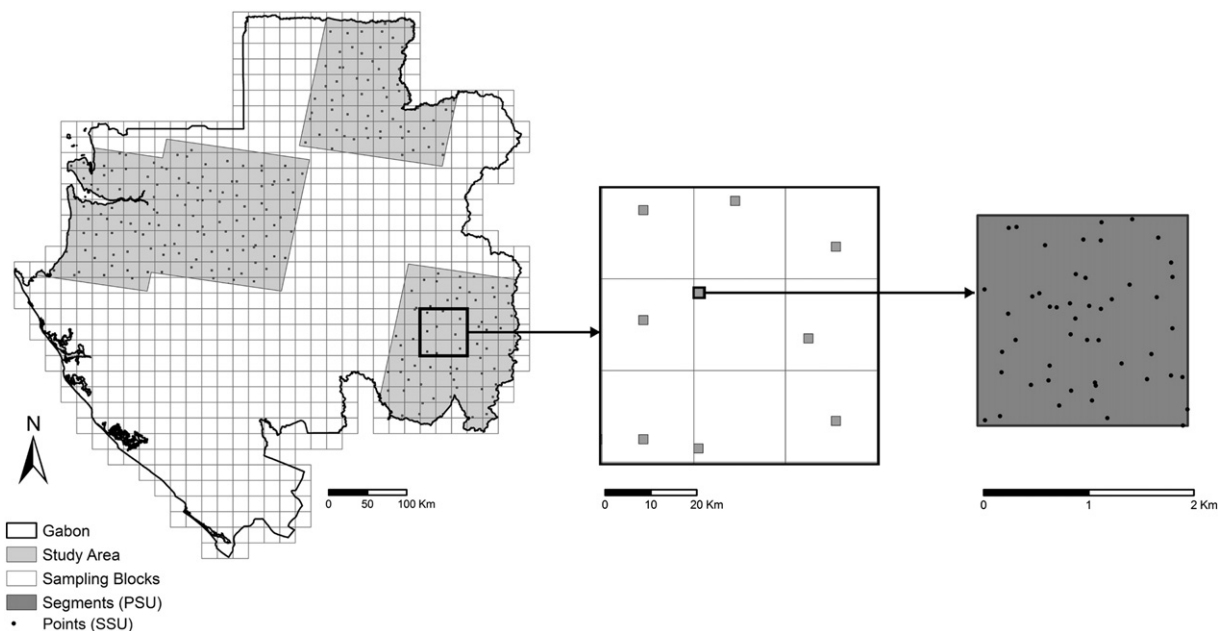


Fig. 3. Identification of segment (PSU) and point (SSU) sample units.

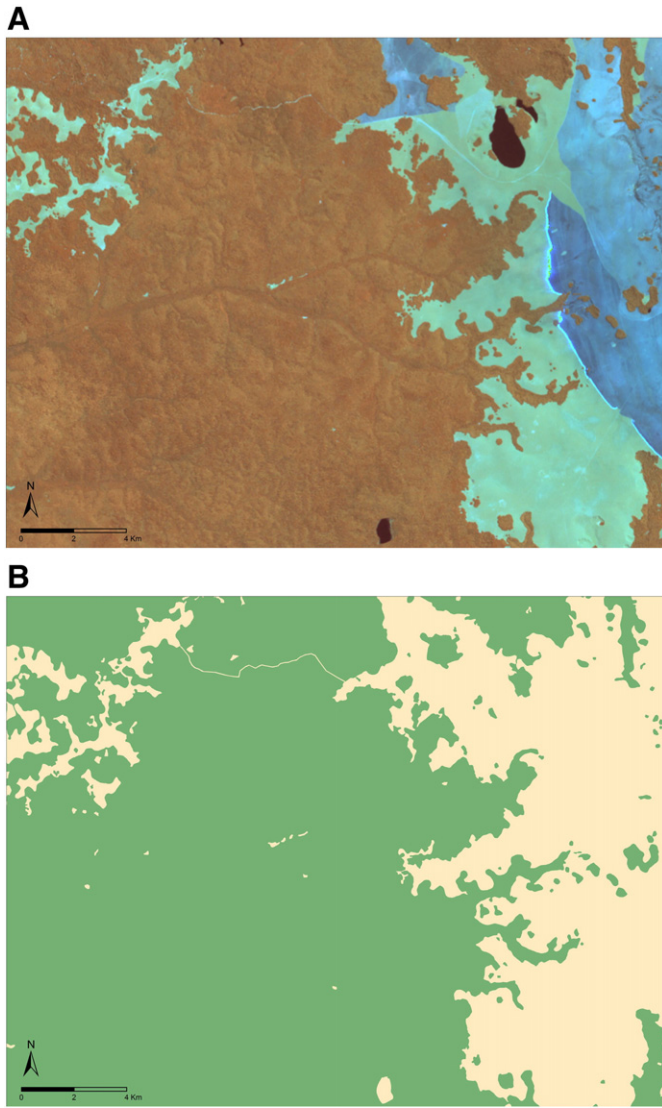


Fig. 4. Example of forest cover map production process with (A) the processed Landsat image (R = Band 4, G = Band 5 and B = Band 7) and (B) classified output (forest in green).

separately according to the forest and non-forest classes using the same methodology as that for 2000. Thus, the area classified as forest in 2000 was also separately classified using the imagery corresponding to reference years 1990 and 2010; the same classification procedure was applied to the areas classified as non-forest in 2000.

3.4. Accuracy assessment

Error matrices were constructed for the 1990, 2000 and 2010 forest cover maps based on paired observations extracted from the forest cover map and the pixel-level reference data.

3.5. Forest cover area and forest cover change estimation

The analyses entailed using two sets of estimators, each with two sampling designs, for each of two response variables. The two estimators were (1) the direct estimator which does not use the map information and (2) the model-assisted regression (MAR) estimator which does use the map information; the two sampling designs were the one-stage design used for the segment-level data and the two-

stage design used for the pixel-level data; and the two response variables were proportion forest cover and net proportion deforestation.

The descriptive term *regression* is commonly used to describe the second set of estimators (Cochran, 1977; Särndal, Swensson, & Wretman, 1992), probably because when the estimators were developed the model of the relationship between the response variable and the predictor variables was most often in the form of a linear regression model. However, any modeling approach, whether explicit or implicit, that produces replicable predictions is generally understood to be acceptable for use with these estimators. For example, Breidt and Opsomer (2000) used local polynomial regression, Zheng and Little (2004) used penalized splines, Lehtonen, Särndal, and Veijanen (2005) used a nonlinear logistic regression model, Särndal (2007) used a calibration approach, and Breidt and Opsomer (2009) used non-parametric and semi-parametric approaches, all while still using the term *regression estimator*.

The forms for the following estimators are similar to those from Gregoire and Valentine (2007, p. 397), although the notation is slightly different. In addition, when sampling is with replacement, as was the case within segments for this study, segment-level finite population correction factors are not used. Further, for sampling among segments, the small finite population correction factor of 0.01 was ignored as per Cochran (1977, p. 25).

3.5.1. Segment-level data, direct estimators

The direct estimators were used with the segment-level reference data to estimate population means for the two response variables: (1) *proportion forest* for which $z_i = y_i^{\text{ref},t}$ is the reference observation for $i \in S_1$ for the t^{th} reference year, and (2) *net proportion deforestation* for which $z_i = y_i^{\text{ref},t_2} - y_i^{\text{ref},t_1}$ is the reference observation for $i \in S_1$ for the interval t_1 to t_2 .

The direct estimators take the forms,

$$\hat{\mu} = \frac{1}{m} \sum_{i \in S_1} z_i \quad (1)$$

and

$$\text{Var}(\hat{\mu}) = \frac{1}{m(m-1)} \sum_{i \in S_1} (z_i - \hat{\mu})^2, \quad (2)$$

where $m = 251$ denotes the number of segments in the first-stage sample. In this manner, proportion forest is estimated for each reference year, and net proportion deforestation is estimated for each time interval.

3.5.2. Segment-level data, model-assisted regression (MAR) estimators

The MAR estimators were used with the combination of the segment-level reference and map data to estimate population means for the two response variables: (1) *proportion forest* for which $z_i = y_i^{\text{ref},t}$ is the reference observation for $i \in S_1$ for the t^{th} year and $\hat{z}_i^{\text{map},t}$ is the corresponding map prediction, and (2) *net proportion deforestation* for which $z_i = y_i^{\text{ref},t_2} - y_i^{\text{ref},t_1}$ is the reference observation for $i \in S_1$ for the interval t_1 to t_2 and $\hat{z}_i = \hat{y}_i^{\text{map},t_2} - \hat{y}_i^{\text{map},t_1}$ is the corresponding map prediction. An initial estimator of the population mean is,

$$\hat{\mu}_{\text{initial}} = \frac{1}{M} \sum_{i=1}^M \hat{z}_i, \quad (3)$$

where $M = 25,100$ is the total number of segments in the population. However, this estimator may be biased as the result of systematic classification error. An estimator of the bias is,

$$\text{Bias}(\hat{\mu}_{\text{initial}}) = \frac{1}{m} \sum_{i \in S_1} (\hat{z}_i - z_i), \quad (4)$$

where $m = 251$ is the number of segments in the first-stage sample. The MAR estimator (Särndal et al., 1992, Section 6.5) is defined as the difference between the initial estimator and the bias estimator and is expressed as,

$$\hat{\mu}_{\text{MAR}} = \hat{\mu}_{\text{initial}} - \text{Bias}(\hat{\mu}_{\text{initial}}) \\ = \frac{1}{M} \sum_{i=1}^M \hat{z}_i - \frac{1}{m} \sum_{i \in S_i} (\hat{z}_i - \bar{z}_i). \quad (5)$$

An estimator of the variance of $\hat{\mu}_{\text{MAR}}$ is

$$\text{Var}(\hat{\mu}_{\text{MAR}}) = \frac{1}{m(m-1)} \sum_{i \in S_i} (\epsilon_i - \bar{\epsilon})^2, \quad (6)$$

where $\epsilon_i = \hat{z}_i - \bar{z}_i$ and $\bar{\epsilon} = \frac{1}{m} \sum_{i \in S_i} \epsilon_i$. In this manner, proportion forest cover is estimated for each reference year, and net proportion deforestation is estimated for each time interval.

3.5.3. Pixel-level data, direct estimators

The direct estimators were used with the pixel-level reference data to estimate the population means for the two response variables: (1) *proportion forest* for which $z_{ij} = y_{ij}^{\text{ref},t}$ is the reference observation for pixel $j \in S_i$ for the t^{th} reference year, and (2) *net proportion deforestation* for which $z_{ij} = y_{ij}^{\text{ref},t_2} - y_{ij}^{\text{ref},t_1}$ is the reference observation for pixel $j \in S_i$ for the interval t_1 to t_2 . The direct estimators take the forms,

$$\hat{\mu} = \frac{1}{m \times n} \sum_{i \in S_i} \sum_{j \in S_i} z_{ij}, \quad (7)$$

where $n = 50$ is the number of pixels sampled in each segment. Thus, the variance estimator is,

$$\text{Var}(\hat{\mu}) = \frac{s_b^2}{m} + \frac{1}{m \times M} \sum_{i \in S_i} \frac{s_i^2}{n}, \quad (8)$$

where for $i \in S_i$, $N_i \approx N = 4644$ is the total number of pixels in each segment,

$$s_i^2 = \frac{1}{n-1} \sum_{j \in S_i} (z_{ij} - \bar{z}_i)^2, \quad (9)$$

and

$$s_b^2 = \frac{1}{m-1} \sum_{i \in S_i} (\bar{z}_i - \bar{\mu})^2, \quad (10)$$

where the terms, $\frac{s_b^2}{m}$ and $\frac{s_i^2}{n}$, are estimates of variances. The forms of the estimators $\hat{\mu}$ and $\text{Var}(\hat{\mu})$ are simplified as the result of several sampling features and assumptions: (i) all segments were the same size, (ii) all segments were considered to contain the same number of pixels, and (iii) any effects of pixels straddling segment boundaries were ignored.

3.5.4. Pixel-level data, model-assisted regression (MAR) estimators

The MAR estimators are used with the combination of the pixel-level reference and map data to estimate the population means for two response variables: (1) *proportion forest* for which $z_{ij} = y_{ij}^{\text{ref},t}$ is the reference observation for pixel $j \in S_i$ for the t^{th} year with corresponding map prediction, $\hat{z}_{ij} = \hat{y}_{ij}^{\text{map},t}$, and (2) *net proportion deforestation* for which $z_{ij} = y_{ij}^{\text{ref},t_2} - y_{ij}^{\text{ref},t_1}$ is the reference observation for $j \in S_i$ for the

interval t_1 to t_2 with corresponding map prediction, $\hat{z}_{ij} = \hat{y}_{ij}^{\text{map},t_2} - \hat{y}_{ij}^{\text{map},t_1}$. An initial estimator of the population mean is,

$$\hat{\mu}_{\text{initial}} = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N \hat{z}_{ij}, \quad (11)$$

where $M = 25,100$ is the total number of segments in the population and for all $i \in S_i$, $N_i \approx N = 4644$ is the number of pixels in each segment. An estimator of the bias resulting from systematic classification error is,

$$\text{Bias}(\hat{\mu}_{\text{initial}}) = \frac{1}{m} \sum_{i \in S_i} (\bar{z}_i - \bar{z}_i), \quad (12)$$

where $\bar{z}_i = \frac{1}{n} \sum_{j \in S_i} z_{ij}$ and $\bar{z}_i = \frac{1}{n} \sum_{j \in S_i} \hat{z}_{ij}$. The MAR estimator is defined as the difference between the initial and bias estimators,

$$\hat{\mu}_{\text{MAR}} = \hat{\mu}_{\text{initial}} - \text{Bias}(\hat{\mu}_{\text{initial}}). \quad (13)$$

Under the assumption that for all $i \in S_i$, $N_i \approx N = 4644$, and that sampling is with replacement within segments, an estimator of the variance is,

$$\text{Var}(\hat{\mu}_{\text{MAR}}) = \frac{s_b^2}{m} + \frac{1}{m \times M} \sum_{i \in S_i} \frac{s_i^2}{n}, \quad (14)$$

where

$$s_i^2 = \frac{1}{n-1} \sum_{j \in S_i} (\epsilon_{ij} - \bar{\epsilon}_i)^2,$$

$$s_b^2 = \frac{1}{m-1} \sum_{i \in S_i} (\bar{\epsilon}_i - \bar{\epsilon})^2,$$

$$\epsilon_{ij} = \hat{z}_{ij} - z_{ij},$$

$$\bar{\epsilon}_i = \frac{1}{n} \sum_{j \in S_i} \epsilon_{ij},$$

and

$$\bar{\epsilon} = \frac{1}{m} \sum_{i \in S_i} \bar{\epsilon}_i.$$

Table 1

Summary of Landsat image data coverage for the selected study area corresponding to Landsat WRS2 P183R61, P183R62, P184R58, P184R59, P185R60 and P186R60.

Reference year	Image date	Area covered [km ²]	Cumulative percentage [%]	Number of Landsat images processed
1990	1990	41729.6	40.7	5
	1989	35442.5	75.3	7
	1988	21045.1	95.8	15
	1987	3158.6	98.9	8
	1985	300.4	99.2	2
	1984	163.0	99.4	4
	No data	639.9	100.0	
2000	2000	94604.4	92.3	13
	1999	1928.9	94.2	2
	2001	5059.6	99.1	8
	2002	791.1	99.9	9
	2003	34.9	99.9	4
	No data	60.4	100.0	
2010	2010	68551.2	66.9	7
	2011	24475.0	90.8	10
	2009	8105.2	98.7	8
	2008	1036.2	99.7	3
	2007	311.5	100.0	4
	No data	0.0	100.0	

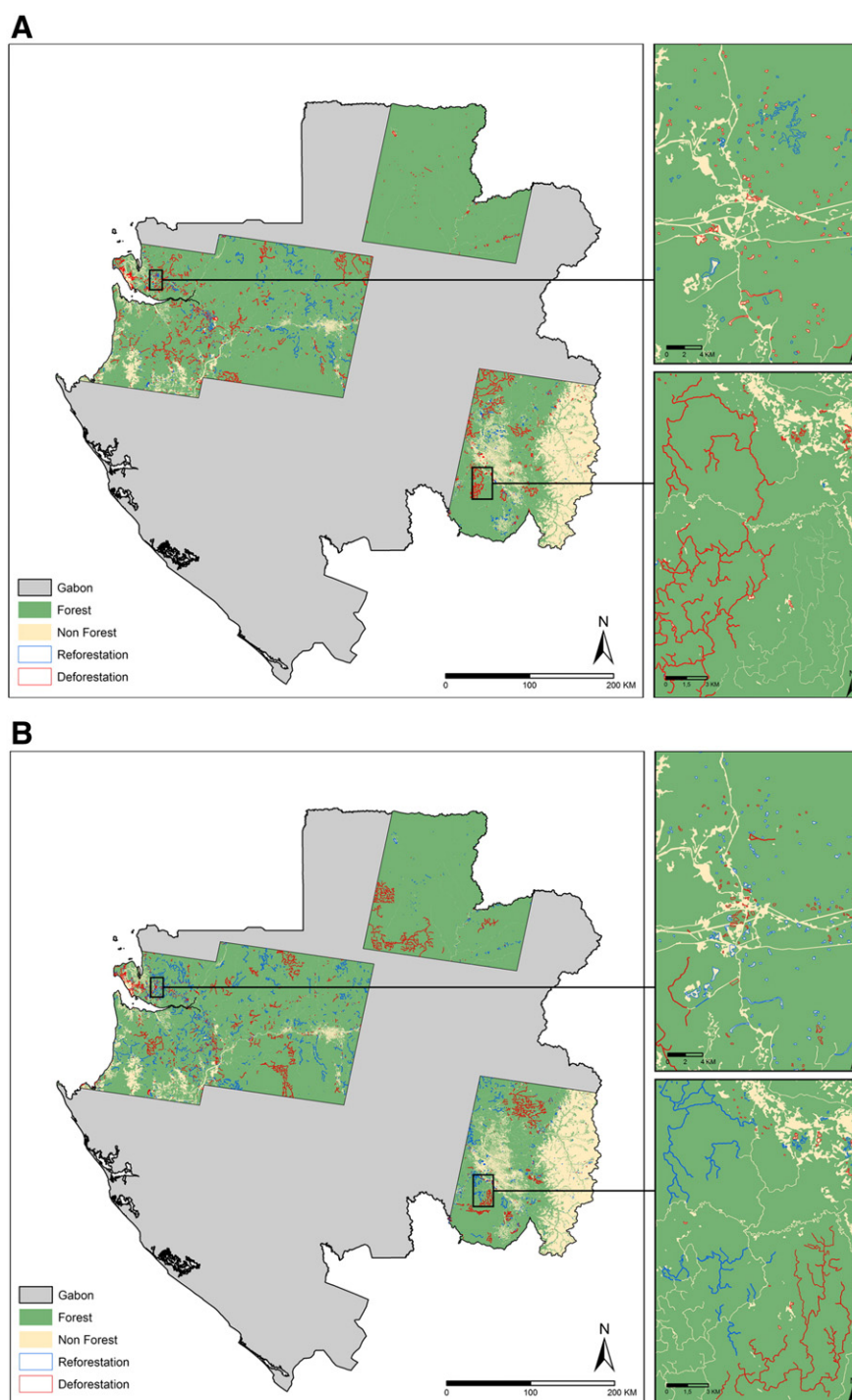


Fig. 5. Forest cover change maps for (A) 1990–2000 and (B) 2000–2010.

4. Results and discussion

4.1. Image acquisition

Overall, 123 Landsat images were required to obtain sufficient cloud free coverage for reference years 1990, 2000, and 2010 due to the large level of cloud cover. An average of six, but as many as nine Landsat images were required to cover the area represented by a single scene. The average cloud cover was 42% for the images used in map production, but reached 55% for WRS2 186/061.

Complete coverage for each reference year was not possible (Table 1). For reference year 2000, cloud-free imagery was obtained

for 93% of the study area; however, for reference year 2010 cloud-free imagery was obtained for only 67% of the study area, and for reference year 1990, the percentage was only 41%. However, 95% of the area could be covered using imagery within two years of the reference year 1990, and nearly 99% within one year of both reference years 2000 and 2010. Overall, less than 1% of the study area could not be covered for any of the reference years with 1990 being the most difficult. These results demonstrate that optical imagery and the Landsat archive in particular are suitable for wall-to-wall forest cover mapping in a cloud-prone country such as Gabon. They also reinforce the benefits of acquiring and maintaining a systematic, time series archive of observations of the Earth's surface. Of particular note, there was no indication in

Table 2
Error matrices for the 1990, 2000 and 2010 forest cover maps based on SSUs ($n = 12550$).

		Reference		Total	User's accuracy
		Forest	Non-forest		
1990	Forest	10,609	124	10,733	0.9884
	Non-forest	161	1656	1817	0.9114
	Total	10,770	1780	12,550	
Producer's accuracy		0.9851	0.9303	Overall accuracy	0.9773
2000	Forest	10,565	117	10,682	0.9890
	Non-forest	173	1695	1868	0.9074
	Total	10,738	1812	12,550	
Producer's accuracy		0.9839	0.9354	Overall accuracy	0.9769
2010	Forest	10,575	103	10,678	0.9904
	Non-forest	170	1702	1872	0.9092
	Total	10,745	1805	12,550	
Producer's accuracy		0.9842	0.9429	Overall accuracy	0.9782

the 1980s and 1990s that Landsat imagery acquired in those years would be so indispensable for forest cover mapping at later dates. Moreover, one Landsat satellite is not sufficient to provide annual cloud-free coverage for a country such as Gabon. Although the lack of satellite data for estimating long-term rates of deforestation may not be seriously detrimental, it will be problematic if forest cover is to be monitored on an annual basis for management and legal enforcement purposes. Thus, the launch of Landsat 8 and especially Sentinel 2a and b are particularly welcome for these applications. Finally, studies such as this one that requires more than 40 Landsat images for each reference year would not be possible without Landsat's free and open data access policy.

4.2. Accuracy assessment

Fig. 5 illustrates the forest cover maps and indicates that changes in the levels of net deforestation measured were extremely small. Construction of error matrices using all pixels contained within segments would have led to the inclusion of a large number of non-independent spatially contiguous observations. Therefore, error matrices were constructed using only the pixels selected for the second-stage sample. The results are detailed in Table 2 and are very consistent across the three forest cover maps. Overall accuracies were all close to 98%, and neither producer nor user accuracies were less than 90%. Furthermore, there were no obvious imbalances in the error distributions, meaning that omission errors were nearly equal to commission errors with the result that bias estimates associated with the initial estimates were small.

The reference data were acquired independently from map production by visual interpretation of the available satellite imagery by a forestry expert with extensive experience. Thus, the reference data can suffer from errors, although such errors are less likely than for the map production process. The reason is that interpreters focused on smaller areas and were able to use data from all available sources. Errors or disagreements with the map are most likely attributable to the following causes:

- Geometry of features detected: the reference data are likely to be more precise, particularly when very fine resolution imagery was available;
- Differences in image acquisition dates: the imagery used to produce the reference data was selected independently from the imagery used for map production with the result that the two image dates may differ by a small number of years;
- Errors in the map or reference data.

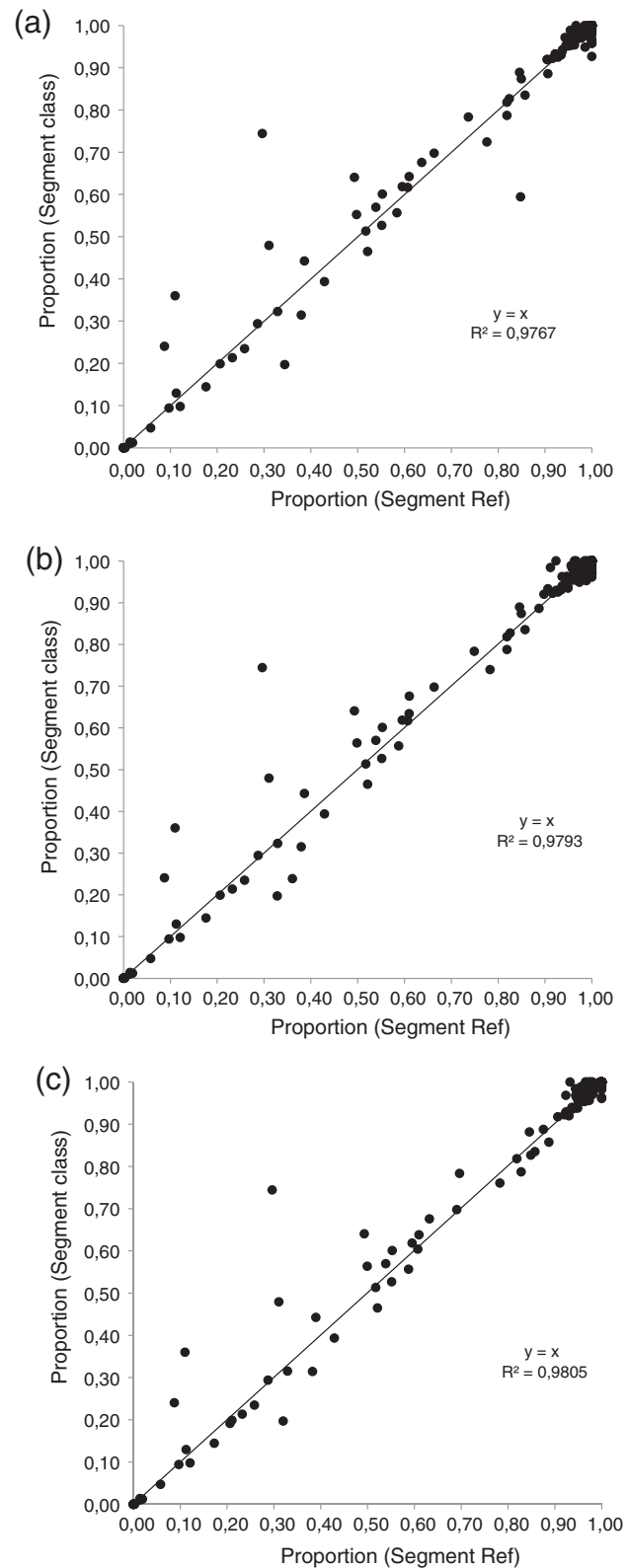


Fig. 6. Comparison of map class (class) and reference (ref) observation forest proportion at the segment level for the (a) 1990, (b) 2000, and (c) 2010 forest/non-forest maps.

However, considering the high level of agreement between the map and reference data, errors may be assumed to be few and production of reference data may be assumed to be possible, particularly when there is a sharp spectral difference between forest, which is almost entirely evergreen in Gabon, and non-forest.

Table 3

Estimates of proportion forest cover and net proportion deforestation from points; estimates in bold indicate estimates that are not significantly different from 0 (SE = Standard Error).

	Forest cover			Forest cover change		
	1990	2000	2010	1990–2000	2000–2010	1990–2010
Direct mean	0.8552	0.8512	0.8508	−0.0041	−0.0003	−0.0044
Direct SE	0.0186	0.0187	0.0188	0.0020	0.0013	0.0030
Map estimate	0.8633	0.8616	0.8613	−0.0017	−0.0003	−0.0020
Bias estimate	0.0029	0.0045	0.0053	0.0015	0.0009	0.0024
MAR estimate	0.8604	0.8571	0.8560	−0.0033	−0.0011	−0.0044
MAR SE	0.0032	0.0031	0.0029	0.0012	0.0012	0.0016

These results were confirmed at the segment-level as shown in Fig. 6. For the forest/non-forest maps for all three reference years, the estimates of forest proportions based on the reference data were similar to the proportions for the segments. However, the maps for each reference year had a few segments for which the differences were large, although systematic errors were not evident. A simple linear regression model fit to the reference observations as the dependent variable and the corresponding predictions as the independent variable (Fig. 6) produced $R^2 = 0.98$, and estimates of the intercept and slope were close to 1 and 0, respectively, thus confirming the results obtained from the error matrices.

4.3. Forest cover and forest cover change estimates

When comparing the direct and the MAR estimates of proportion forest for the pixel-level dataset (Table 3), two results were noteworthy: (i) the large accuracies of the maps were indicated by the similarities between the direct and the map-based estimates and by the small bias estimates, and (ii) the smaller standard errors (SE) for the MAR estimates relative to the direct estimates could be attributed to the relevance of the auxiliary information on which the maps are based.

When comparing the direct and MAR estimates of net proportion deforestation, five results were noteworthy: (i) the large accuracies of the maps were indicated by the similarities between the direct and the map-based estimates and by the small bias estimates, (ii) the adjustments for estimated biases produced MAR estimates that were closer to the direct estimates than the map-based estimates, (iii) the relative equality of the direct estimates of SEs and the MAR estimates of SEs was attributed to the fact that the SEs were already very small, i.e., very little improvement was even possible, (iv) the very small SEs for estimates of net proportion deforestation relative to the SEs for estimates of proportion forest were attributed to the beneficial effects of using the same reference pixels for all three classifications; this result is similar to the benefit obtained using a paired *t*-test as opposed to the standard *t*-test, and (v) at the approximate $\alpha = 0.05$ level of significance, none of the 2000–2010 estimates (direct and MAR) were significantly different from 0. The latter result was not surprising considering the even smaller estimate of net deforestation compared to that of 1990–2000. The fact that the 1990–2010 direct expansion estimate (−0.44%) was not significantly different from 0 was more surprising.

Table 4

Estimates of proportion forest cover and net proportion deforestation from segments; estimates in bold indicates estimates that are not significantly different from 0 (SE = Standard Error).

	Forest cover			Forest cover change		
	1990	2000	2010	1990–2000	2000–2010	1990–2010
Direct mean	0.8568	0.8534	0.8532	−0.0034	−0.0002	−0.0036
Direct SE	0.0185	0.0186	0.0186	0.0021	0.0009	0.0027
Map estimate	0.8633	0.8616	0.8613	−0.0017	−0.0003	−0.0020
Bias estimate	0.0027	0.0042	0.0049	0.0015	0.0007	0.0023
MAR estimate	0.8606	0.8574	0.8564	−0.0032	−0.0010	−0.0043
MAR SE	0.0028	0.0026	0.0025	0.0009	0.0008	0.0012

However, this was in contrast to the MAR estimate (−0.44%) for which the SE was much smaller (0.30% versus 0.16%).

These results were further confirmed by the segment-level estimates (Table 4) which were very similar to the pixel-level estimates for the proportion forest cover and net proportion deforestation, although SEs were even smaller. Both 2000–2010 estimates were not significantly different from 0, and all other estimates were significantly different from 0 which is consistent with the level of net deforestation observed.

Although the SEs in Table 3 did not so indicate, the among-segments portions of the variance estimates dominated the within-segments portions of the variance estimates. A minor contribution to this result may be that among-segments variance estimates were slightly inflated as a result of using a systematic rather than a simple random sampling design to select the first-stage segments (Särndal et al., 1992). The smallness of the within-segments variance relative to the among-segments variance should not be surprising given the large accuracies of the classifications and the relatively large within-segments reference sample size, $n = 50$. For future considerations, even smaller overall SEs for both direct and MAR estimates could perhaps be obtained for the same number of pixels by selecting more segments but with fewer pixels within each segment. However, for this study, the objective of small standard errors was certainly achieved, so in this sense the design was appropriate. In addition, there was little, if any, prior knowledge of the relative sizes of the among- and within-segments variances.

5. Conclusions

The use of the model-assisted regression estimator reduced the variances of the proportion forest cover estimates by a factor of approximately 50, meaning that to obtain equivalent results using only a sampling approach, the sample size would have to be increased by the same factor. In addition, there were differences between the map-based and MAR estimates of net deforestation despite the very large accuracies for the forest cover maps. Thus, even though large mapping accuracies can be achieved, map-based estimates without adjustment for estimated biases should be used cautiously. Nevertheless, all results exhibited the same overall trend: direct expansion estimates could be produced rapidly and used to report reliable estimates of net proportion deforestation, while wall-to-wall maps could be used to refine those estimates and to support more detailed investigations.

In addition, pixel-level estimates exhibited slightly greater SEs than segment-level estimates, but the differences were small, particularly when the forest cover maps were used as auxiliary information. Therefore, a two-stage sampling approach was justified for collecting reliable forest cover reference data to estimate proportion forest cover and net proportion deforestation.

The results confirmed the generally small level of net deforestation expected in Gabon. Further, the estimates of net proportion deforestation were significantly different from 0 for all estimates for the period 1990–2000, whereas they were all not significantly different from zero for the period 2000–2010. The smaller rate of net proportion deforestation estimated for the latter 10 years could be explained by the creation of national parks and the implementation of forest concession management plans from 2000 onward, although the link between Gabonese environmental policies and the estimated reduced level of forest loss should be further explored.

However, the coefficients of variation for net proportion deforestation estimates were large compared to the coefficients for the proportion forest cover estimates. This result is likely attributable to a weaker relationship between the reference and map data, probably for the reasons outlined in Section 4.2 (mismatch in geometry, temporal differences, and actual interpretation errors). The estimated level of net proportion deforestation was small, approximately 0.04% per annum for the 1990–2000 period.

The nature of forest dynamics in Gabon makes finding a sound basis for stratification difficult because the majority of gross deforestation is linked to forest exploitation and can occur at any time in forest concessions which are scattered over the entire country. A more thorough understanding of deforestation drivers and causes is required but was beyond the scope of this study.

Finally, the approach developed for 38% of Gabon was subsequently applied to the entire country for 1990 and 2000; the analyses for 2010 are still progress. Initial results confirm those obtained for the 38% with a similar estimate of the net proportion deforestation rate. The 95% confidence interval width represents approximately 0.25% of the proportion forest cover estimates and represents 88.4% of the overall area of the country, making forest cover in Gabon even greater than had been previously thought.

These results demonstrate that despite Gabon's heavy cloud cover, imagery for the entire study area could be acquired. However, the large amount of cloud cover meant that on average six Landsat images were required to cover the area of a single Landsat scene. Nevertheless, the methodology was sufficiently robust and simple to implement that it can be readily implemented in Gabon and other similar tropical countries.

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