DEMONSTRATION OF SEMI-AUTOMATED APPROACHES FOR MONITORING NATIONAL TROPICAL DEFORESTATION

FOREST CARBON, MARKETS AND COMMUNITIES (FCMC) PROGRAM

MARCH 2015

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ACRONYMS AND ABBREVIATIONS

BURs	Biennial Update Reports
C	cloud
DT	decision tree
Ems	end members
GHG	greenhouse gas
GLAD	Global Land Analysis and Discovery
GV	green vegetation
IDEAM	Institute of Hydrology, Meteorology and Environmental Studies
IMAZON	Instituto do Homem e Meio Ambiente da Amazônia
IPCC	International Panel on Climate Change
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
MINAM	Peru's Ministry of Environment
MMU	minimum-mapping unit
MODIS	Moderate Resolution Imaging Spectromoter
MRV	Measurement, Reporting and Verification
NCs	National Communications
NDFI	Normalized-Difference Fraction Index
NDVI	normalized-difference vegetation index
NDWI	normalized-difference water index
NPV	Non-green vegetation
REDD+	Reduced Emissions from Deforestation and Degradation, plus the role of conservation, sustainable forest management and enhancement of forest carbon stocks
RMSE	root mean square error
S	soil
Sh	shade
SMA	spectral mixture analysis
TOA	top-of-atmosphere
UFCCC	United Nations Framework Convention on Climate Change

UMD	University of Maryland
USAID	United States Agency for International Development

ABSTRACT

International agreements of the United Nations Framework Convention on Climate Change (UNFCCC) seek to reduce national forest-related emissions via activities and policies on Reduced Emissions from Deforestation and Degradation, plus the role of conservation, sustainable forest management and enhancement of forest carbon stocks (REDD+). These agreements require countries to develop systems to monitor and report changes in forest cover and carbon stocks via systems of Measurement, Reporting and Verification (MRV) that include forest monitoring. We demonstrate three methodologies proposed for semi-automated monitoring of deforestation at the national level: ClasLite, ImgTool, and Global Land Analysis and Discovery (GLAD). Methods are based on Landsat satellite images and compared for two common study areas in Mexico and Colombia. High-resolution images from RapidEye were interpreted for comparison with the methods' results in deforestation estimates. Comparisons with samples of interpreted points from the high-resolution images indicate overall high levels of accuracy and agreement; however, an evaluation of the deforestation rates and patterns over the entire study area indicate significant differences, especially in Mexico, which contains dry forest and a large portion of secondary forest fallow. We provide a discussion of implications for monitoring and recommendations for further study.

1.0 INTRODUCTION

1.1 REDD+ MRV

International agreements of the United Nations Framework Convention on Climate Change (UNFCCC) as well as bi-lateral agreements or agreements with donor institutions seek to reduce national forest-related emissions via activities and policies on Reduced Emissions from Deforestation and Degradation, plus the role of conservation, sustainable forest management, and enhancement of forest carbon stocks (REDD+). These agreements require countries to develop systems to monitor and report changes in forest cover and carbon stocks. In the context of REDD+ these monitoring systems are built specifically to conduct activities known as Measurement, Reporting, and Verification (MRV).

The International Panel on Climate Change (IPCC) provides detailed technical guidance on different aspects of conducting greenhouse gas (GHG) inventories in a MRV system, including field and statistical methods, equations, and default values (IPCC, 2006). The IPCC is thorough on topics of carbon stocks, calculation of GHGs by combining data on stocks and land-use change, and uncertainty estimation. It is less thorough on the estimation of land-use change. On this subject, the IPCC provides general criteria including a recognition of the appropriateness of the use of satellite.

The IPCC also has communicated quality principles for a MRV system: transparency, completeness, consistency, comparability, and accuracy. These principles are discussed in other reports (e.g., GOFC, 2015; FCMC, 2015; and Steininger et al., 2015). Another important factor is latency: how quickly estimates can be generated and updated. Reporting to the UNFCCC occurs every four years for National Communications (NCs) and every two years, starting in December 2014, for Biennial Update Reports (BURs). These reports should include information for the most recent year.

1.2 SEMI-AUTOMATED METHODOLOGIES FOR FOREST MONITORING

Several satellite-based methods for forest monitoring have incorporated greater levels of automation recently. These methods may better enable countries to meet the quality principles, especially consistency over reporting periods as well as requirements of latency. While it is theoretically possible for some of these methods to be fully automated, in practice, they all have required some level of analyst input when applied to produce national maps of deforestation. For this reason, these methods can be considered semi-automated.

Medium-resolution data represent the most common sources for national forest monitoring because they currently offer an optimal combination of appropriate resolution, acquisition frequency, coverage and cost, as well as other technical characteristics. Among these data, Landsat remains the most common data source for monitoring land-use change, including forest-related changes. Landsat data extend back to 1972 at a 60-meter resolution and to 1984 at a 30-meter resolution. Landsat thoroughly archives images – and with a 16-day revisit time, multiple images for any site are obtainable. Data from the reflectance bands in the visible, near-infrared, and middle-infrared bands are useful for characterizing leaf cover, canopy shading, inundation, exposed soil, non-photosynthetic vegetation, as well as clouds and haze. Finally, the no-cost access to the data places no constraints on data access. Consequently, most forest-monitoring methods are based on Landsat, and this report specifically addresses examples of Landsat-based methodologies.

Automation is important because it can reduce the time and resources needed to produce or update estimates of deforestation. Automation mostly occurs in the steps of pre-processing, data transformation, and post-processing. Pre-processing steps include conversion of the original satellite-image values to reflectances, which involves corrections for effects of atmospheric conditions and effects of sun and view angles. Data transformations vary considerably among methods and include calculation of spectral indices, differences between years in image values of indices, spectral mixture analysis (SMA), and calculation of temporal metrics. Post-processing includes re-coding classification output values to a common scheme, combining recoded results with previous map products if the analysis is an update, merging classification results from neighboring scenes to form a regional or national mosaic, and applying filters or eliminating small patches to a defined minimum-mapping unit (MMU).

Following data transformation and preceding post-processing is the classification process itself. This is where methods still mostly require analyst input, and the reason methods are usually not fully automated in practice. For supervised-classification approaches, analysts interpret images and create training sites. These are areas within the images that analysts define as being in certain classes, such as deforestation versus forest persistence, etc. These training sites are then the basis for calculation of class signatures or automated decision trees (DTs). An iterative process is common, in which analysts enter training sites, evaluate the classification output, and adjust training sites until a satisfactory classification result is obtained.

Rule-based methods seek to simplify this process. They are based on a set of thresholds of values applied to reflectances or values of indices, SMA outputs, etc. A set of default thresholds may exist, although in practice they usually require image-specific, user-defined threshold rules. As in supervised approaches, an iterative process is common, testing the use of different rule sets to obtain a satisfactory result.

For either approach, consistency must be sought via minimizing variance in analysts' interpretation of images from different parts of the study area and different years. Consistency is especially important when updates are conducted with new analysts. Both the supervised and rule-based approaches theoretically can be fully automated, where after some point input of analyst interpretation is no longer required. Supervised approaches can be fully automated by applying the derived class signatures or DTs from a previous analysis to new data. Rule-based approaches can be fully automated by applying a fixed set of rules. In practice, this approach usually does not lead to satisfactory results, and thus some analyst input is required. In some cases a compromise approach that seeks to limit the amount of analyst input has been taken. This approach includes using the training sites from a previous time period and adding a moderate amount of new ones to conduct an update in supervised approaches, or constraining the range of rule adjustments in rule-based approaches.

This paper demonstrates the application of three methods to estimate deforestation, which involve significant levels of automation. Each method is based on Landsat. Two of the methods apply SMA at a scene-by-scene level. The third method mines the Landsat data archive, creates a set of multi-temporal metrics, and uses these in a supervised DT. As noted above, all three are commonly applied in a semi-automated manner although potentially can be fully-automated.

1.3 THREE METHODS

ClasLite

Stanford University provides ClasLite, which has been applied in various countries such as Peru and Colombia (Asner et al., 2009). It is based on no-cost software that is available to users who complete a training exercise. It works with images from two different dates, applies SMA, and then assigns pixels to change or no change based on a set of rules.

ClasLite begins with an atmospheric correction using the 6S program (Vermote et al., 2015), with an optional additional step to normalize effects of haze variations within individual scenes. The latest version uses Fmask (Zhu et al., 2012) to mask clouds. Additional masking may be applied later during the classification step. ClasLite applies SMA by referring to a library of spectral end members (EMs) for green vegetation (GV), Non-green vegetation (NPV), and soil (S). The results are images of the fraction of cover of each of the features, which can be displayed, interpreted, and classified as if they were reflectance images. To reduce artifacts that may cause within-image variations in GV, ClasLite rescales the GV values based on the percent tree cover values from the global GLAD product (Hansen et al., 2013). The fractional values as well as the reflectance values and SMA's root mean square errors (RMSEs) are used in the classification step.

For classification, ClasLite provides a default set of rules to distinguish forest and deforestation over two dates, as well as to mask additional clouds, cloud shadow, water, and wetlands. These are:

Static forest cover:

$$\text{Forest: } GV \geq 80 \text{ and } S < 20 \tag{1}$$

$$\text{Non-forest: } GV < 80 \text{ or } S \geq 20 \tag{2}$$

Deforestation step 1:

$$GV_1 - PV_2 \geq 25 \tag{3a}$$

$$\text{or } S_1 \leq 5 \text{ and } S_2 - S_1 \geq 15 \tag{3b}$$

$$\text{or } PV_2 < 80 \text{ and } NPV_2 - NPV_1 \geq 20 \tag{3c}$$

Deforestation step 2 (removing false positives):

$$PV_{1,2} \geq 80 \text{ and } NPV_{1,2} \geq 35 \text{ and } RMSE_{1,2} \geq 6 \tag{4a}$$

$$\text{or } S_2 \geq 50 \text{ and } S_2 < 100 \text{ and } PV_2 > 0 \tag{4b}$$

$$\text{or } NPV_2 - NPV_1 < 10 \text{ and } \mathrm{abs}(Refl_{1b1} - Refl_{2b1}) > 300 \tag{4c}$$

$$\text{and } \mathrm{abs}(Refl_{1b4} - Refl_{2b4}) < 700$$

$$\text{and } \mathrm{abs}(Refl_{1b4} - Refl_{2b4}) > 200$$

where GV, NPV, and S are the percent coverage of green vegetation, non-green vegetation, and soil, respectively; RMSE is the root mean square error of the SMA; Refl is spectral reflectance; subscripts 1 and 2 are the first and second image dates; and subscripts b1 and b4 are Landsat bands one, i.e., blue, and four, i.e., near-infrared. ClasLite's pre-processing, data transformation, and application of default rules can be automated on a scene-by-scene basis. More common is to not accept the defaults and to seek a different set of thresholds via trail-and-error.

ImgTools

The Brazilian nongovernmental organization Instituto do Homem e Meio Ambiente da Amazônia (IMAZON) provides ImgTools, which is also available as a no-cost available to the public. It also works with images from two different dates, applies SMA and then rules to assign pixels to forest change or no change. It uses Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006) combined with an algorithm from Carlotto et al. (1999) to correct images atmospherically. Initial cloud masking is then applied using cloud and shade fractions obtained from SMA (Souza et al., 2013). Further cloud masking may be applied during the classification step.

In ImgTools SMA, EMs are derived from the image itself rather than from a library of field-based spectra. Unlike ClasLite, ImgTools calculates the fraction of shade (Sh) and cloud (C). ImgTools also calculates a vegetation index called the Normalized-Difference Fraction Index (NDFI). This is akin to the normalized-difference vegetation index, which is calculated from the near-infrared (NIR) and red reflectances (NDVI = (NIR-red)/(NIR+red)). The NDFI combines the fractional components of the pixel:

$$NDFI = (GV - (NPV + S)) / (GV + NPV + S) \qquad (5)$$

where GV, NPV, and S are the percent coverage of green vegetation, non-green vegetation, and soil, respectively. All of the above steps are automated – and like ClasLite, the remaining steps may or may not involve analyst interpretation. The default rule-set for ImgTools is:

Cloud:

$$C \geq 10 \qquad (6)$$

Water:

$$GV \leq 5 \text{ and } (NPV + S) < 15 \qquad (7)$$

Non-forest:

$$GV \geq 85 \qquad (8)$$

Forest (within remaining area):

$$\text{Intact: } NDFI \geq 75 \qquad (9a)$$

$$\text{Degraded: } NDFI < 75 \qquad (9b)$$

Where C, GV, NPV, and S are the percent coverage of cloud, green vegetation, non-green vegetation, and soil, respectively; and NDFI is the Normalized-Difference Fraction Index in percent. Thus, forest cover is estimated for individual dates, and change is estimated by combining the results of the static forest estimates. This step is followed by a set of rules to remove dis-allowed transitions, such as change from water to non-forest, assumed to be associated with changing water levels rather than land-use, and change from forest to non-forest near cloud edges. Earlier versions of ImgTools used DTs in a supervised classification rather than the rule-based approach, and this approach is still an option in the latest version.

GLAD

The University of Maryland (UMD) developed the Global Land Analysis and Discovery (GLAD) (Potapov et al., 2012, 2014a, 2014b), which has been installed in several national government laboratories for application in national monitoring. It has yielded nationwide deforestation assessments for the Democratic Republic of Congo, Indonesia, and Peru (e.g., Potapov, 2014a; Margono et al., 2014), as well as a global map of tree-cover loss (Hansen et al., 2013).

GLAD differs from the above approaches at the highest level in that it mines the entire Landsat data archive for a study area, is applied at the level of mosaics or entire study areas, creates a large set of temporal metrics, and produces a time-series of forest change for all selected dates within a study period. Metrics are based on the archive's image reflectances, NDVI, normalized-difference water index (NDWI)—a water index akin to NDVI but replacing red with middle-infrared—and temperature from

Landsat's thermal band. The metrics are used in a supervised classification to estimate percent tree cover and tree-cover loss, forest cover and deforestation, or other types of land-cover change of interest. While much of the process is automated, it involves analyst interpretation during the classification step.

GLAD applies atmospheric correction by normalizing top-of-atmosphere (TOA) reflectances to long-term averages of atmospherically-corrected reflectances from the Moderate Resolution Imaging Spectromoter (MODIS). This approach purposely removes some of the seasonal variations in Landsat data. While using data from multiple seasons is very useful for mapping vegetation types, subtle differences within seasons may cause difficulties in estimating inter-annual changes. GLAD applies proprietary cloud-masking and haze-detection algorithms. GLAD calculates a comprehensive set of temporal metrics, reducing the data volume, from which users can select for use in analysis. Metrics relate to trends over image dates, maximum differences over the series, and ranks of values over the series. A full list of metrics is provided in Potapov et al. (2014b).

GLAD applies DTs via an iterative, supervised approach. The DT classifies whether there has been any forest change over the study period, and the year of change is assigned based on evaluation of minimum annual NDVI throughout the period. Because of the approach to normalization of the image archive, and because the archive then has been translated into a set of temporal metrics, it is possible to apply a derived DT to a new time period once the new data have been similarly pre-processed and transformed into the metrics. Alternatively, one can take the existing set of training sites and add new ones only for new areas of change.

2.0 METHODS

2.1 DEMONSTRATION AREAS

We selected two areas for demonstration, which include a range of heavily-settled lands to tropical forest frontiers. The first is within the Yucutan Peninsula, Mexico, mostly south and east of Merida, from 90.18 W 21.13 N to 86.95 W 19.31 N. This area contains semi-deciduous and dry forest with mostly flat terrain. The area includes a gradation to low-stature dry forest and has natural sandstone formations that have created a series of small sinkholes and water bodies. Land use is small-scale agriculture and settlements, with some small plantations and many sites in various stages of secondary forest regrowth.

The second area is in the Colombian Amazon, mostly Florencia in the Caqueta pronvince, from 76.11 W 2.14 N to 72.52 W 0.39 N. This area contains lowland evergreen forest with mostly flat terrain. It includes natural grasslands and several rivers with natural regrowth of woody vegetation on their banks. The area includes both frontier deforestation and long-established settlements and agriculture and has a relatively modest amount of agricultural forest fallows.

Satellite images for Colombian area typically have major gaps caused by clouds, resulting in limited options for image selection within specific years. Images for the Mexican area are less cloudy, although they reveal major variations in reflectance patterns based on vegetation seasonality. Each study area extends over two Landsat scenes, each with a total area of approximately 450,000 km^2, roughly half of which is forested.

2.2 DATA

Landsat images were selected for circa 2000 and circa 2014, with particular dates chosen based on the portion of cloud-free coverage and season. Selected images are listed in Table 1. Within each study area, four images from circa 2014 were selected from the RapidEye archive. RapidEye has a spatial resolution of 5 meters and includes spectral bands in the visible and near-infrared. These data are useful for evaluating classifications, since individual trees can be observed, allowing for easy interpretation of land cover. The selected images cover areas of active deforestation frontiers, have minimal cloud coverage, and are close to the same dates as the Landsat data. Selected RapidEye images are also listed in Table 1 in Section 6.

2.3 APPLICATION AND EVALUATION OF THREE METHODS

Classification using ClasLite was conducted by Colombia's Institute of Hydrology, Meteorology and Environmental Studies (IDEAM). IDEAM's analysts have four years of experience in interpreting tropical forest Landsat images and in the use of ClasLite. ClasLite's penultimate version, which is very similar to its current version 3.0, was used. Pre-processing and application of the SMA was performed per the method's protocol (ClasLite, 2014). The default thresholds listed in Section 1 were used to define the classification rules for both static forest and loss.

IMAZON, the provider of the tool conducted classification using ImgTools. Pre-processing and application of the SMA was performed per the method's protocol (Souza and Siqueira, 2013). Thresholds to define classification rules were selected via an iterative process of application and evaluation of results. Three iterations were executed before obtaining the final results.

Classification using GLAD was conducted by UMD for Mexico and Colombia and by Peru's Ministry of Environment (MINAM) using GLAD's standard pre-processing and metric-calculation protocols (Potapov 2014a, 2014b). This approach contrasts ClasLite and ImgTools, which were implemented specifically for this study. Where conducted by UMD, classifications were extracted from national products that UMD created for these two countries, rather than from their global map. Change estimates for 2000 to 2013 were produced by aggregating the annual change results. These results were derived from a single change analysis conducted for 2000 to 2013. The analyses were iterative, supervised DTs that were applied over each entire country. Output classifications were for all change over the time period, subsequently partitioned to individual years using the annual-minimum-NDVI criterion. All three methods were applied at the pixel level, and resulting classifications were not filtered.

2.4 COMPARISON OF PRODUCTS

This study focuses specifically on the detection of deforestation and not on differences in definitions of initial forest extent, cloud-masking abilities, or other aspects of land-cover change estimation. Thus, we excluded variations in results that were not specific to detection of deforestation. We excluded variations by defining a baseline extent of where the methods agreed on cloud-free observations and forest cover.

Classification raster files for all study areas and methods were recoded into a common scheme. ClasLite and ImgTools both yielded estimates of forest extent, in circa 2000 and 2014, as well as estimates of areas obscured by clouds and cloud shadow on either date. We combined the results of these two methods to produce a benchmark map of where both agreed on forest cover in 2000 and cloud- and shadow-free observations.

Each method produced estimates of forest loss that occurred inside and outside the agreed-forest baseline area. To exclude those outside, we intersected each raster file of forest loss with the agreed-forest baseline. We named the output area deforestation and the remaining forest area forest persistence. Deforestation files were combined into a single file to report the distribution and areas of agreement and disagreement among the three.

To produce strata for sampling within areas of estimated deforestation and forest persistence, we aggregated all areas of deforestation from the three methods. We then created a buffer of two pixels within deforestation and persistence to avoid locating sample points near edges. The resulting two masks were combined with the extent of the high-resolution images to create two sampling masks for each demonstration area. Within each, 150 points for deforestation and persistence were randomly selected. For each point, we interpreted the high-resolution images and assigned labels to identify points of deforestation, persistence and undetermined. For deforestation sub-classes, points interpreted as active farmland versus secondary forest fallow were identified. A cross-tabulation of these points with the classification results for the latter date from each method was produced for comparison.

3.0 RESULTS

3.1 RATES AND PATTERNS

Estimates of total rates of deforestation over the 13-year period varied among the three methods much more for Mexico than for Colombia (see Table 2 in Section 6). Those for Mexico ranged from 584 km^2 from ClasLite to 2454 km^2 from GLAD. Those for Colombia and Peru ranged from 1594 km^2 from ClasLite to 1756 km^2 from ImgTools. ClasLite estimated the least deforestation in Mexico, and GLAD estimated much more than both ClasLite and ImgTools. In Mexico, differences in estimates of the distribution of deforestation were widespread (see Figure 1 in Section 6). For example, ImgTools estimated large patches of deforestation in the north-western corner of the study area, where the other two did not. GLAD estimated many areas of deforestation across the eastern third of the area, mostly within the eastern Landsat scene, where ClasLite and ImgTools estimated sparse deforestation. As a consequence, there is relatively little overlap in the estimates, indicated by large portions of estimates where only one of the three estimated deforestation in Figures 2 and 3.

Estimates of rates for Colombia are more consistent among the three (Table 2), as were the estimated distributions (Figure 4). Here the majority of deforestation shows overlaps of two or three methods' results (Figures 5, 6). This trend can be seen in the large deforestation frontier in the center of the area as well as a second frontier in the northeastern corner of the area, where estimated deforestation among all three methods mostly overlaps. The main area of disagreement in distribution is where ImgTools estimated deforestation along Caqueta river in the south of the eastern Landsat scene.

3.2 COMPARISON WITH HIGH-RESOLUTION DATA

Locations of the selected high-resolution images relative to the 2000 forest baseline area in Mexico are shown in Figure 7. Interpreted sample points are shown in Figure 8 and displayed over the high-resolution images in Figure 9. The same series for Colombia is shown in Figures 10, 11, and 12. For both study areas, comparisons of these points with the results from each method suggest overall high accuracies, a high level of agreement, and consistently conservative estimates of deforestation (Tables 3, 4). In Mexico none of the 150 forest points were classified as deforested by any of the methods, and in Colombia only four forest points were classified as deforested.

In Mexico, a clear difference in the results is found for deforested areas that were interpreted as being active farmland versus secondary forest in circa 2013. For farmland points, all three methods identified deforestation for 82 to 90 percent of the points. The secondary forest sites are areas where methods agreed on the presence of forest cover in circa 2000 and, according to the interpretation of the high-resolution images, had been cleared and subsequently reverted to secondary forest by circa 2013. GLAD estimated deforestation for all of the 35 secondary-forest points, whereas ClasLite and ImgTools estimated forest persistence for 35 and 34 points, respectively. In Colombia, all three methods estimated deforestation for 96 to 97 percent of the points interpreted as active farmland. Only two secondary forest points were sampled in Colombia; for these, ImgTools and GLAD estimated forest persistence for one, and ClasLite estimated deforestation for both.

4.0 DISCUSSION

4.1 INTERPRETATION OF THE DEMONSTRATIONS

The findings from this study are different when referring to the entire area of each demonstration area versus referring to the sampled points of interpreted high-resolution images. For the full study-area results, the findings from Colombia are encouraging. They demonstrate general agreement in rates and distribution of deforestation. There are nonetheless some significant areas of disagreement – for example where ImgTools estimated deforestation along the Caqueta River, although these are exceptions. Classification with ImgTools was done through three iterations for this study. In a national application, we expect that one or more additional iterations would be conducted, that they would be conducted by analysts more familiar with the area, and that this result could easily be changed. The similar results obtained by using only the default thresholds in ClasLite are also encouraging.

There are at least two likely explanations for the greater disagreement in the Mexican demonstration. First is the deciduousness of the forests in this area. In such cases, the selection of particular images for analysis is very important for methods that process one image per time period. We selected images that were the least cloudy and from within the same season, the northern winter. However, within-season differences in leaf display are important and can be unpredictable, as they are based on each year's weather. The images from circa 2000 showed signals of less leaf cover than in circa 2013 for the same forests, and non-forest areas in 2013 showed relatively high levels of greenness. This combination leads to a lack of significant decreases in greenness; additionally, methods that seek a significant decrease, such as ClasLite and ImgTools, can be expected to provide inconsistent estimates of conversion from forest to non-forest.

While the Colombian Landsat images were relatively easy to interpret for this analysis, the Mexican ones were difficult in certain places. The gradations of forest deciduousness and high portions of secondary forests in particular are problematic for image interpretation. In an application within a national MRV system, further iterations likely would be conducted and done so with closer familiarity of the study area and coordination with local experts. Different image dates may also be selected, which could influence the application of the two scene-by-scene methods.

The main difference among the methods applied in Mexico is for secondary forest. This difference is indicated by the sampled points of interpreted high-resolution data and is likely the main explanation for inconsistent results across the area. The results for the secondary forest points may appear severe but should be of relatively little concern in the context of monitoring within a national MRV system. Monitoring likely will be conducted on a bi-annual to annual basis. These shorter time periods are not sufficient for a forested site to be cleared, abandoned or fallowed, and have advanced secondary forest present at the time of the later image. Rather than having sites that appear forested in both the initial and later image, the later image will be active farmland or some other land cover with a strong soil signal. We expect that in annual to bi-annual monitoring ClasLite and ImgTools results would be more similar to the results for the active farmland points only. GLAD estimated deforestation for the secondary forest sites mostly likely because of a strong deforestation signal detected earlier within the 13-year period, since the application of GLAD used the entire archive for these areas.

The most consistent result among the methods and study areas is the overall conservativeness of the results. Almost all differences between the classification results and the interpreted high-resolution data are cases of omitting deforestation in sites that were interpreted as non-forest, or secondary forest fallow, in the second date. Among the point-sample sites, there was only one case of committing deforestation to sites interpreted as forest in the second date. Conservative estimation is generally acceptable, although this must be consistent during update analyses, which may be difficult to ensure. Olofsson et al. (2014) and others provide methods for adjusting estimates of deforestation by accounting for such biases.

A companion report discusses the implications of these and other methods for the IPCC's five quality principles for an MRV system: transparency, completeness, consistency, comparability, and accuracy. We see all three of these methods as highly transparent; their underlying concepts and descriptions of applications are reported in multiple publications. Their specific application in a national system, e.g., particular parameters such as threshold rules applied or training sites and multi-temporal metrics used, can be included in documentation accompanying national reports. Close to complete coverage should be possible in most areas; however, completeness in very cloudy areas will be more easily achievable with data-mining approaches such as in GLAD. Accuracy can be reported using appropriate sampling schemes and high-resolution data such as those used here or obtained by aerial or field surveys.

Consistency and comparability are the most difficult principles to define and demonstrate. In part, comparability is a matter of clear national definitions and demonstrating alignment of image interpretation and/or rules sets with these definitions. Consistency and comparability both require some demonstration that interpretation or the application of methods do not change over different countries, study areas or over time. All of these methods can be applied consistently. In the case of ClasLite, we demonstrated application of default rules that presumably would not change over time; however, in practice, analysts have usually adjusted the rules, as was done for the application of ImgTools. A possible approach to increase consistency could be to divide a country into strata, where within each stratum a non-changing set of rules can be applied. For GLAD, training sites from a previous analysis can be carried forward with modest additions. This approach would maintain the bulk of the data used to drive a classification algorithm, in this case DTs. The Peruvian government has used this approach for updating its national deforestation estimates to 2013.

4.2 RECOMMENDATIONS FOR FURTHER INVESTIGATION

This study has demonstrated varying levels of agreement and disagreement among deforestation estimates derived from three satellite-based methods proposed for application in national MRV systems. Results indicate that the methods are:

- consistently conservative in deforestation estimation;
- relatively consistent in deforestation estimation in areas of active farmland within evergreen forest; and
- less consistent in deforestation estimation in areas of deciduous forest and areas with large portions of secondary forest cover.

The inconsistencies in areas of deciduous and secondary forests possibly could be reduced by experimenting with the use of images from different dates for ClasLite and ImgTools and by applying them at an annual to bi-annual time step. All of the methods' applications can be documented and validated to meet IPCC quality principles. All have potential for consistent application for updating analyses for new time periods, as well as for automating such approaches – and this is an area of active research.

The findings from the comparisons of full-area results versus comparisons with the interpreted high-resolution data suggest different conclusions. The high-resolution data suggest a high level of consistency in rates and distribution among the methods, as well as accuracy. However, the full-area results reveal substantial differences in the estimates of rates and distribution. Many of these differences are in areas of secondary forest, although not all. This finding suggests that a selection of high-resolution data from other parts of the demonstration areas may lead to different conclusions. This concept should be explored further, and a recommendation to do so appears in the list below.

This study provides a first demonstration of these three methods over common study areas and analysis dates. Further exploration of applications of these methods, and possibly others, would be valuable. We conclude with recommendations for further study divided into those that could be done as a continuation with moderate effort (items 1 – 3) and those that imply the need for a substantial research activity (items 4 – 8).

Continuation:

1. Allow for iterative adjustments to default rules in ClasLite and additional iterations to adjust rules in ImgTools.
2. Add an example with montane deforestation – for example in Peru.
3. Interpret points across the Landsat images beyond the extents of the acquired high-resolution data, using a new stratified-random sampling scheme and interpreting both Landsat dates for deforestation versus forest persistence.

New research:

1. Randomly select and interpret high-resolution data based on where methods' results agree and disagree, i.e., select images after all deforestation analyses are completed.
2. Apply ClasLite and ImgTools at an annual to bi-annual time step and aggregate results, i.e., in a manner more similar to the application of GLAD and more similar to expected applications within national MRV systems.
3. Compare consistency in applications by different analysts, e.g., for ClasLite and ImgTools compare selected thresholds, for GLAD compare signatures of training sites and for all compare classification results.
4. Compare national or subnational products, especially in more difficult areas such as mountainous, deciduous and secondary forest areas, which may be possible for portions of Mexico, Colombia, Peru, and Brazil, pending possible future public releases of completed products.
5. Test potential for consistent application over time, for example for ClasLite and ImgTools the use of fixed rules within subnational strata and for GLAD the application of a derived DT to a new time period – all topics of partners' current research and possible paths to full automation of satellite-based deforestation monitoring.

Many countries are currently attempting to apply semi-automated methods to monitor their forests. However, few have compared approaches, and few studies such as this exist for them to refer to. This study has demonstrated three methods in two areas. Further demonstrations and assessments, preferably conducted in partnership with relevant countries, would be valuable contributions to global progress on national capacities for forest monitoring.

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6.0 TABLES AND FIGURES

TABLE 1. LOCATIONS AND DATES OF LANDSAT AND RAPIDEYE HIGH-RESOLUTION IMAGES USED FOR THE STUDY.

	Source	Epoch	Path-row / ID	date
Mexico				
	Landsat-7	c. 2000	019-046	04/21/00
		c. 2000	020-046	11/06/00
		c. 2013	019-046	01/14/14
		c. 2013	020-046	01/21/14
	Rapid Eye	c. 2013	15298757	01/22/14
		c. 2013	15216001	01/13/14
		c. 2013	15483912	02/14/14
		c. 2013	15374524	01/26/14
Colombia				
	Landsat-7	c. 2000	007-059	01/30/01
		c. 2000	008-059	01/05/01
		c. 2013	007-059	03/31/14
		c. 2013	008-059	09/11/13
	Rapid Eye	c. 2013	15351418	01/28/14
		c. 2013	15351484	01/28/14
		c. 2013	14181094	10/05/13
		c. 2013	14998158	12/24/13

TABLE 2. COMPARISON OF AREAS OF DEFORESTATION AND LEVELS OF OVERLAP FOR THE MEXICAN AND COLOMBIAN DEMONSTRATION AREAS.

a. Colombia

Deforestation	Area (km^2)	Area (%)
ClasLite	1,594	5.3
ImgTools	1,756	5.9
GLAD	1,647	5.5
Average	1,666	5.6

Overlap	Area (km^2)	Area (% of aggregate)
1+	2,317	100
2+	1,468	63
3	992	43

b. Mexico

Deforestation	Area (km^2)	Area (%)
ClasLite	584	2.1
ImgTools	1,628	5.7
GLAD	2,454	8.7
Average	1,555	5.5

Overlap	Area (km^2)	Area (% of aggregate)
1+	3,519	100
2+	933	27
3	370	11

TABLE 3. COMPARISON OF ESTIMATIONS FOR THE MEXICAN DEMONSTRATION AREA OF FOREST PERSISTENCE AND DEFORESTATION FROM CIRCA 2000 TO CIRCA 2013 COMPARED TO INTERPRETED POINTS OF HIGH-RESOLUTION RAPIDEYE IMAGES FROM CIRCA 2013.

RapidEye images were visually interpreted to estimate locations of active agriculture (Defor: agric); secondary forest regrowth (Defor: secondary); and mature forest (Persistence). Sums of both forms of deforested land in circa 2013 are provided (Defor: all). Percentages are for user's accuracy (right column) and producer's accuracy (bottom row).

a. ClasLite	Classification		
Interpreted	**Persistence**	**Deforestation**	**%**
Persistence	150	0	100
Defor: agric	20	94	82
Defor: secondary	35	0	0
Defor: all	55	94	63
Un-ID	1	0	
%	73	100	

b. ImgTools	Classification		
Interpreted	**Persistence**	**Deforestation**	**%**
Persistence	150	0	100
Defor: agric	16	98	86
Defor: secondary	34	1	3
Defor: all	11	138	93
Un-ID	0	1	
%	93	100	

TABLE 4. COMPARISON OF ESTIMATIONS FOR THE COLOMBIAN DEMONSTRATION AREA OF FOREST PERSISTENCE AND DEFORESTATION FROM CIRCA 2000 TO CIRCA 2013 COMPARED TO INTERPRETED POINTS OF HIGH-RESOLUTION RAPIDEYE IMAGES FROM CIRCA 2013.

RapidEye images were visually interpreted to estimate locations of active agriculture (Defor: agric); secondary forest regrowth (Defor: secondary); and mature forest (Persistence). Sums of both forms of deforested land in circa 2013 are provided (Defor: all). Percentages are for user's accuracy (right column) and producer's accuracy (bottom row).

a. ClasLite	**Classification**		
Interpreted	**Persistence**	**Deforestation**	**%**
Persistence	150	4	97
Defor: agric	0	138	100
Defor: secondary	0	2	100
Defor: all	0	140	100
Un-ID	0	6	
%	100	97	

b. ImgTools	**Classification**		
Interpreted	**Persistence**	**Deforestation**	**%**
Persistence	151	3	98
Defor: agric	5	133	96
Defor: secondary	1	3	75
Defor: all	6	136	96
Un-ID	1	5	
%	96	98	

c. GLAD	**Classification**		
Interpreted	**Persistence**	**Deforestation**	**%**
Persistence	150	4	97
Defor: agric	14	124	90
Defor: secondary	1	1	50
Defor: all	15	125	89
Un-ID	0	6	
%	91	97	

FIGURE 1. DIFFERENCES AMONG ESTIMATES OF THE DISTRIBUTION OF DEFORESTATION IN THE MEXICAN DEMONSTRATION AREA FROM THREE DIFFERENT METHODS: TOP – GLAD, MIDDLE – IMGTOOLS, BOTTOM – CLASLITE. "FOREST" IS THE AREA OF AGREED FOREST COVER IN CIRCA 2000, AND "DEFOR" IS DEFORESTATION BETWEEN CIRCA 2000 AND CIRCA 2013.

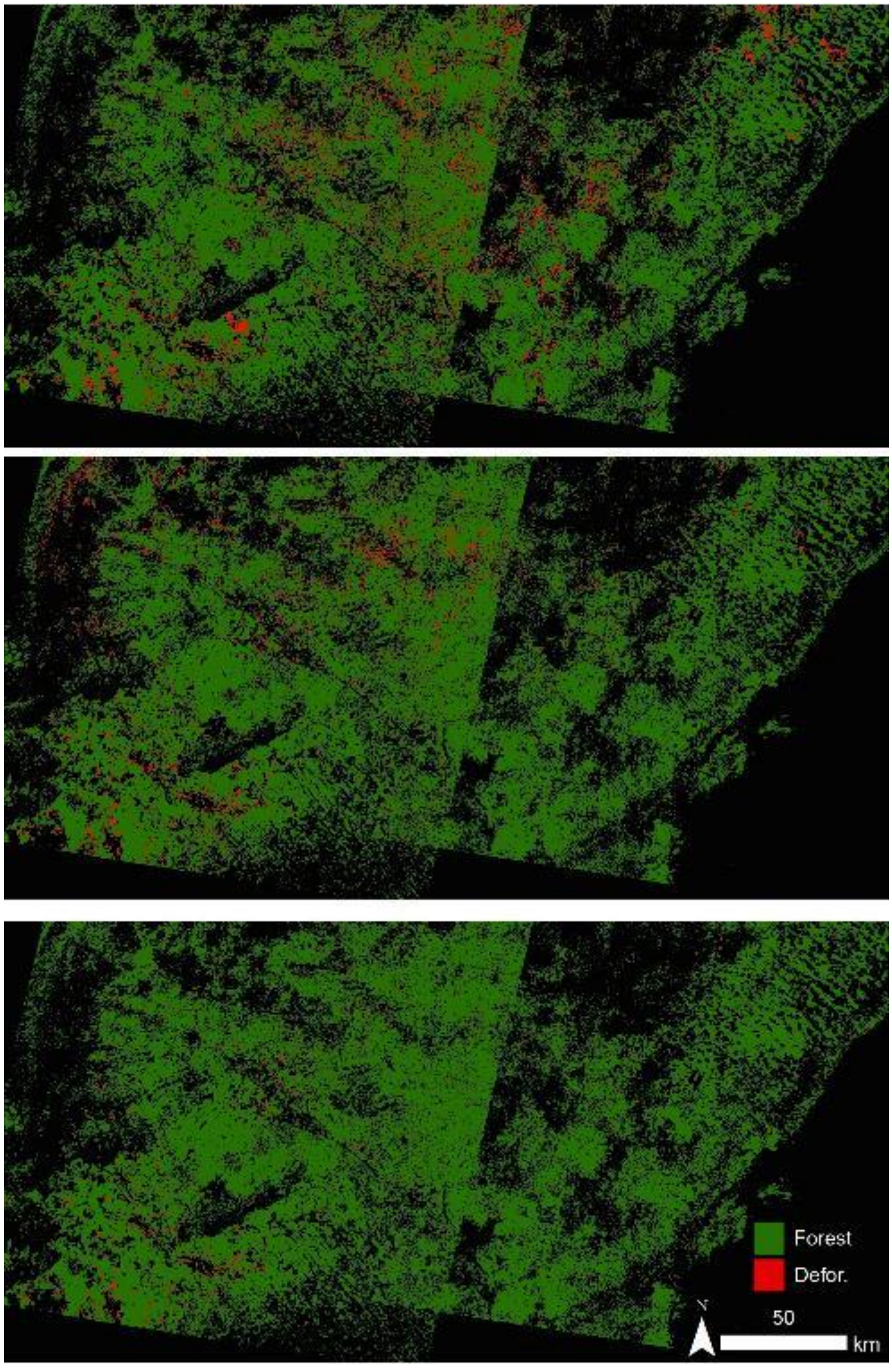

FIGURE 2. AREAS OF AGREEMENT AMONG ESTIMATES OF THE DISTRIBUTION OF DEFORESTATION IN THE MEXICAN DEMONSTRATION AREA FROM THREE DIFFERENT METHODS: CLASLITE, IMGTOOLS, AND GLAD. GREEN IS THE AREA OF AGREED FOREST COVER IN CIRCA 2000, AND BLACK IS NON-FOREST OR NO-DATA. NUMBERS INDICATE THE NUMBER OF METHODS' PRODUCTS THAT INDICATE DEFORESTATION IN A GIVEN SITE.

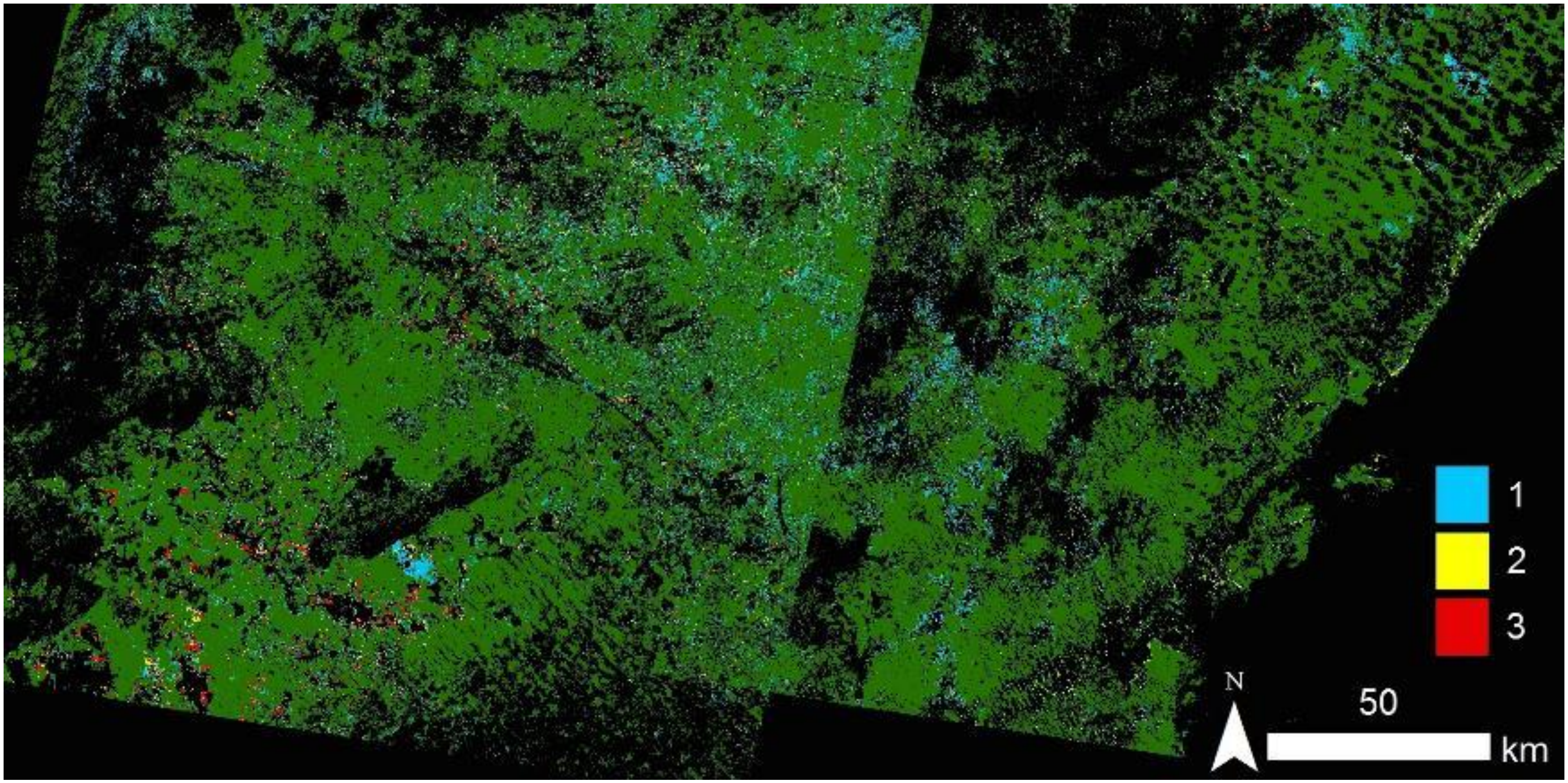

FIGURE 3. DETAIL AREA FOR AREAS OF AGREEMENT AMONG ESTIMATES OF THE DISTRIBUTION OF DEFORESTATION IN THE MEXICAN DEMONSTRATION AREA FROM THREE DIFFERENT METHODS: CLASLITE, IMGTOOLS, AND GLAD. GREEN IS THE AREA OF AGREED FOREST COVER IN CIRCA 2000, AND BLACK IS NON-FOREST OR NO-DATA. LEGEND IS THE SAME AS IN FIGURE 2.

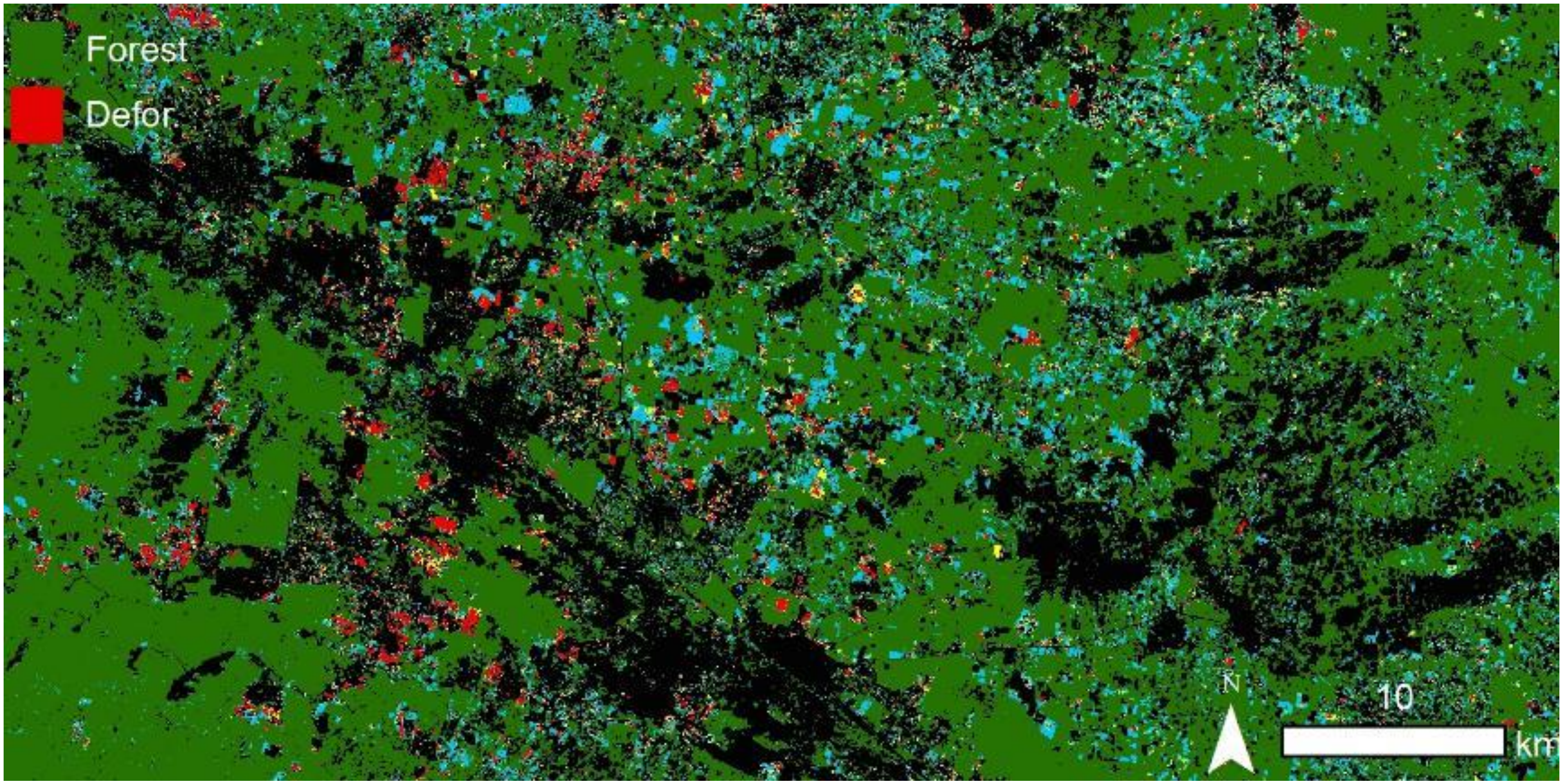

FIGURE 4. DIFFERENCES AMONG ESTIMATES OF THE DISTRIBUTION OF DEFORESTATION IN THE COLOMBIAN DEMONSTRATION AREA FROM THREE DIFFERENT METHODS: TOP - GLAD, MIDDLE – IMGTOOLS, BOTTOM – CLASLITE. "FOREST" IS THE AREA OF AGREED FOREST COVER IN CIRCA 2000, AND "DEFOR" IS DEFORESTATION BETWEEN CIRCA 2000 AND CIRCA 2013.

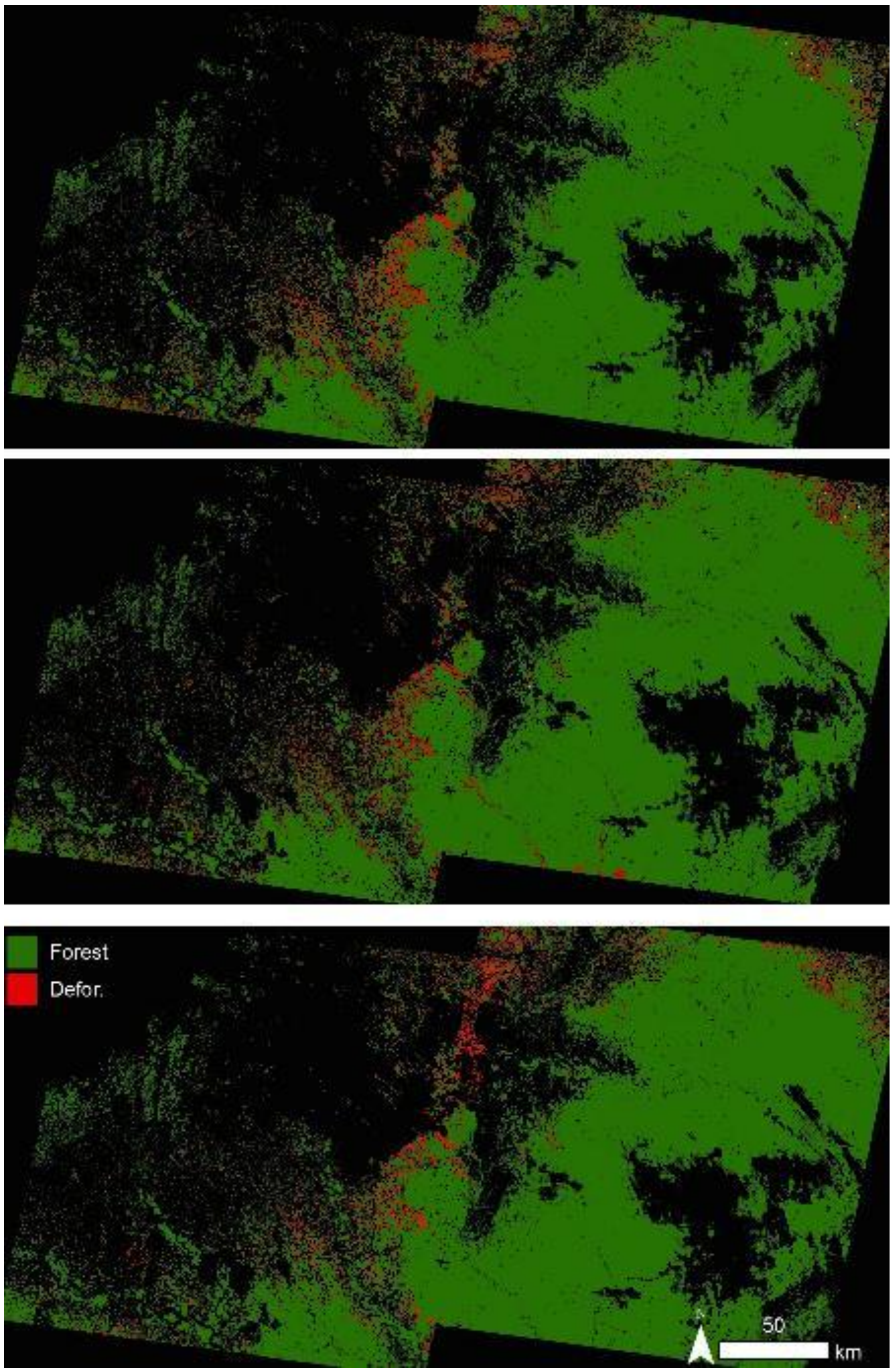

FIGURE 5. AREAS OF AGREEMENT AMONG ESTIMATES OF THE DISTRIBUTION OF DEFORESTATION IN THE COLOMBIAN DEMONSTRATION AREA FROM THREE DIFFERENT METHODS: CLASLITE, IMGTOOLS, AND GLAD. GREEN IS THE AREA OF AGREED FOREST COVER IN CIRCA 2000, AND BLACK IS NON-FOREST OR NO-DATA. NUMBERS INDICATE THE NUMBER OF METHODS' PRODUCTS THAT INDICATE DEFORESTATION IN A GIVEN SITE.

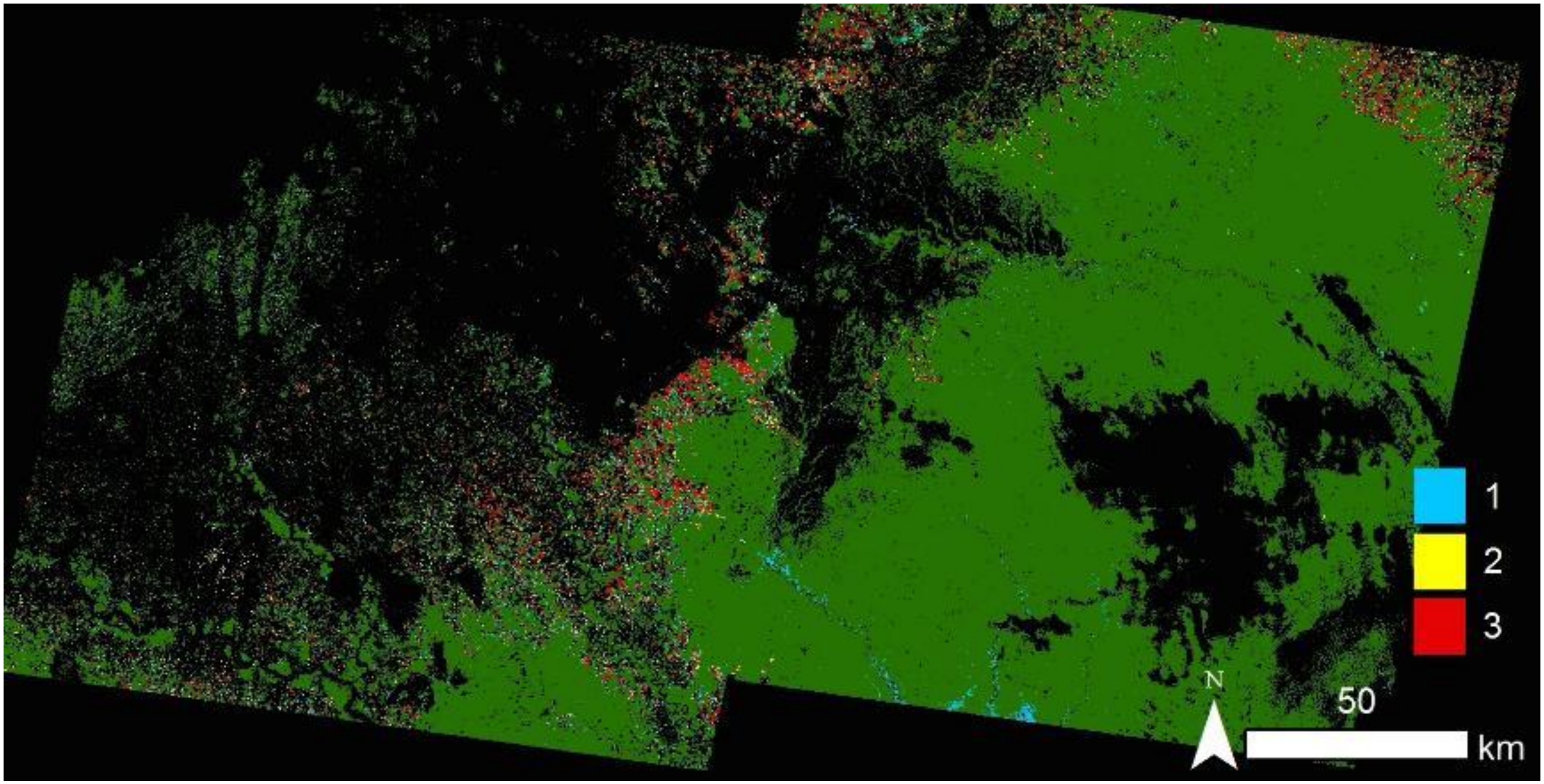

FIGURE 6. DETAIL AREA FOR AREAS OF AGREEMENT AMONG ESTIMATES OF THE DISTRIBUTION OF DEFORESTATION IN THE MEXICAN DEMONSTRATION AREA FROM THREE DIFFERENT METHODS: CLASLITE, IMGTOOLS, AND GLAD. GREEN IS THE AREA OF AGREED FOREST COVER IN CIRCA 2000, AND BLACK IS NON-FOREST OR NO-DATA. LEGEND IS THE SAME AS IN FIGURE 5.

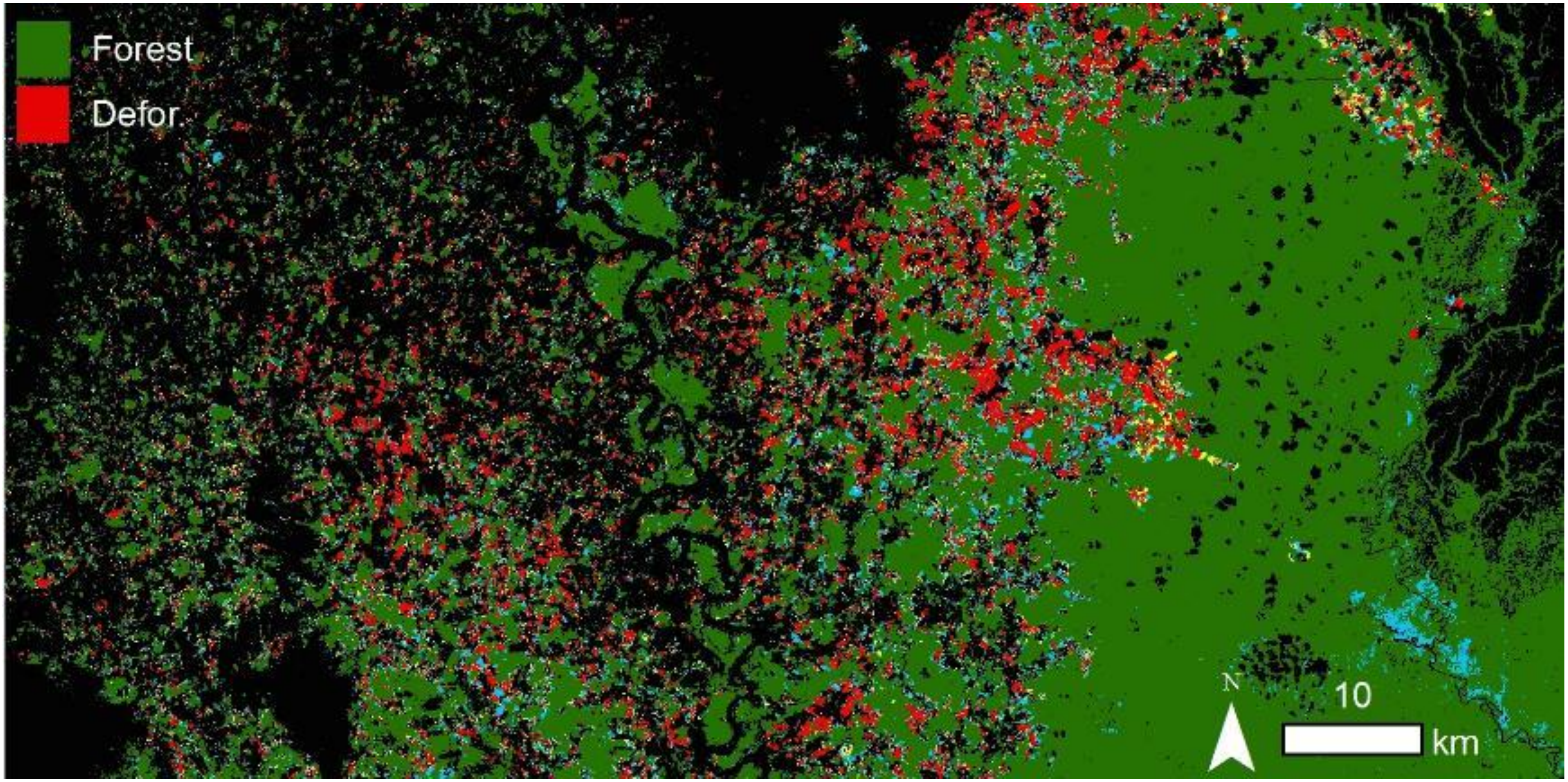

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FIGURE 7. DISTRIBUTION OF HIGH-RESOLUTION IMAGES FROM RAPIDEYE FOR THE MEXICAN DEMONSTRATION AREA. IMAGES ARE COLOR COMPOSITES, 10-KM WIDE EACH, SUPERIMPOSED OVER THE AGREED FOREST DISTRIBUTION FOR CIRCA 2000 (GREY) AND NON-FOREST (BLACK).

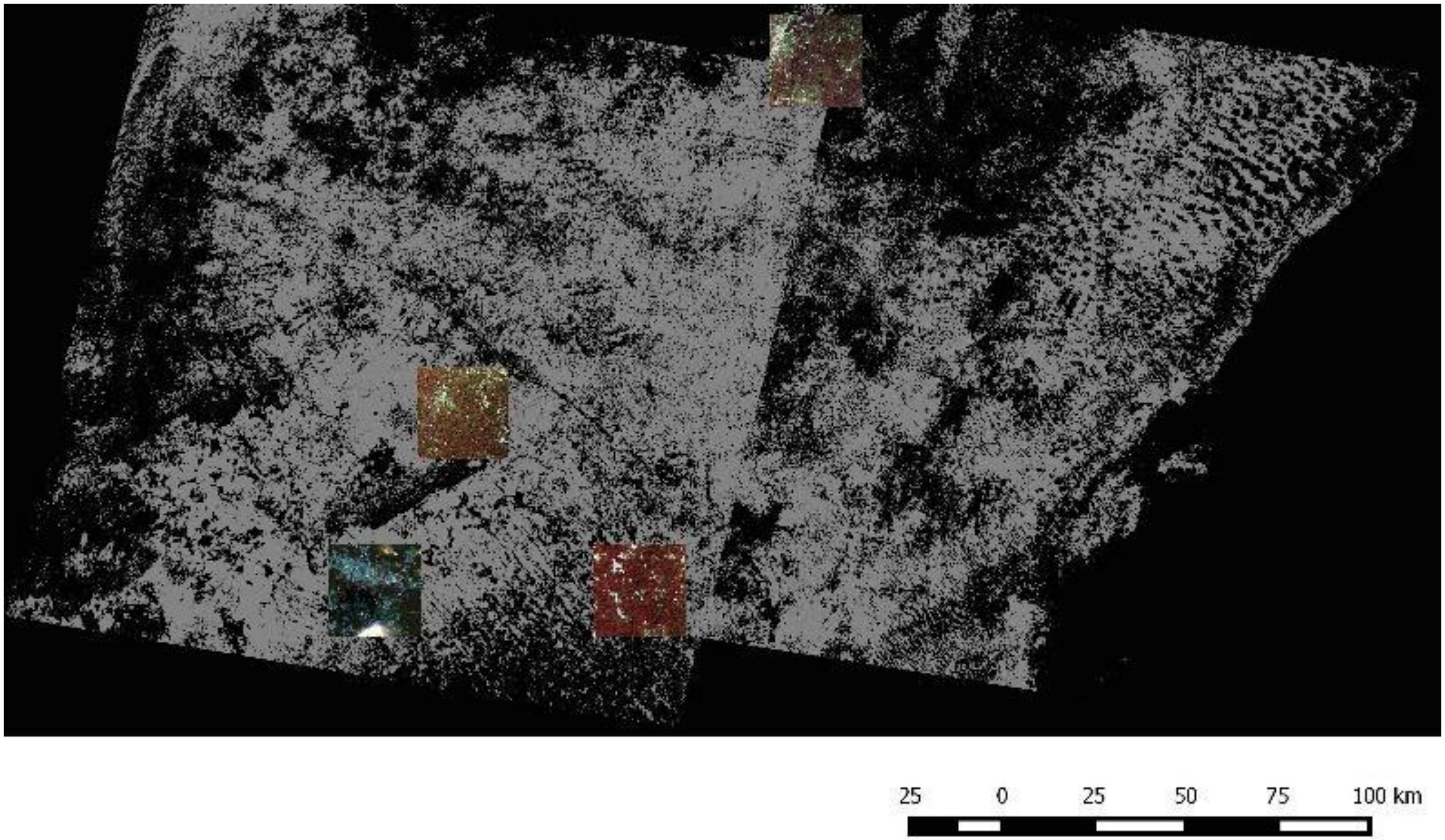


FIGURE 8. DISTRIBUTION OF POINTS OF HIGH-RESOLUTION IMAGES FROM RAPIDEYE VISUALLY INTERPRETED FOR THE MEXICAN DEMONSTRATION AREA. POINTS ARE: GREEN – FOREST, RED – ACTIVE FARMLAND, YELLOW – SECONDARY FOREST OR FALLOW. POINTS ARE SUPERIMPOSED OVER THE AGREED FOREST DISTRIBUTION FOR CIRCA 2000 (GREY) AND NON-FOREST (BLACK).

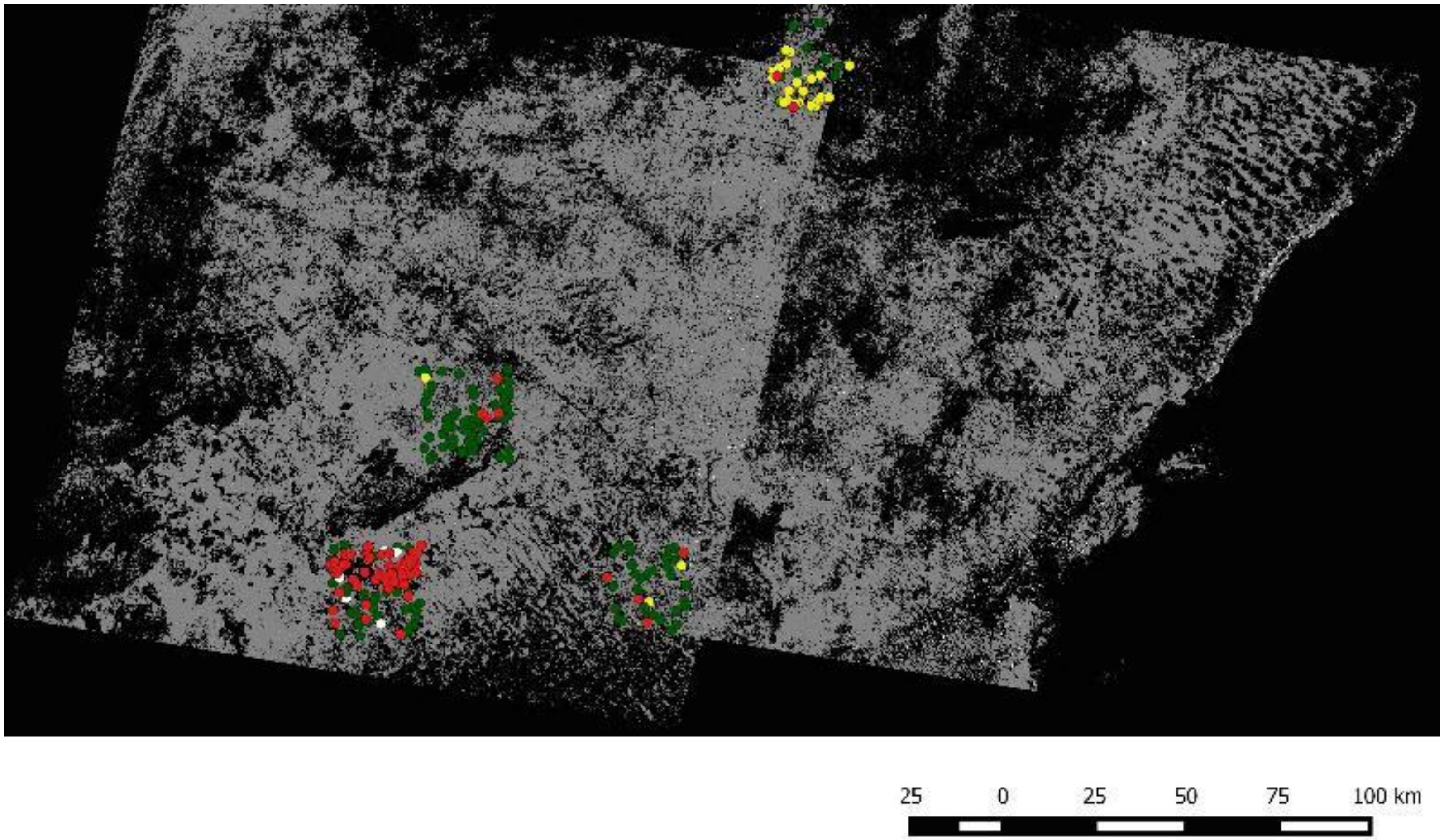


FIGURE 9. HIGH-RESOLUTION IMAGES FROM RAPIDEYE WITH POINTS VISUALLY INTERPRETED FOR THE MEXICAN DEMONSTRATION AREA. POINTS ARE: GREEN – FOREST, RED – ACTIVE FARMLAND, YELLOW – SECONDARY FOREST OR FALLOW.

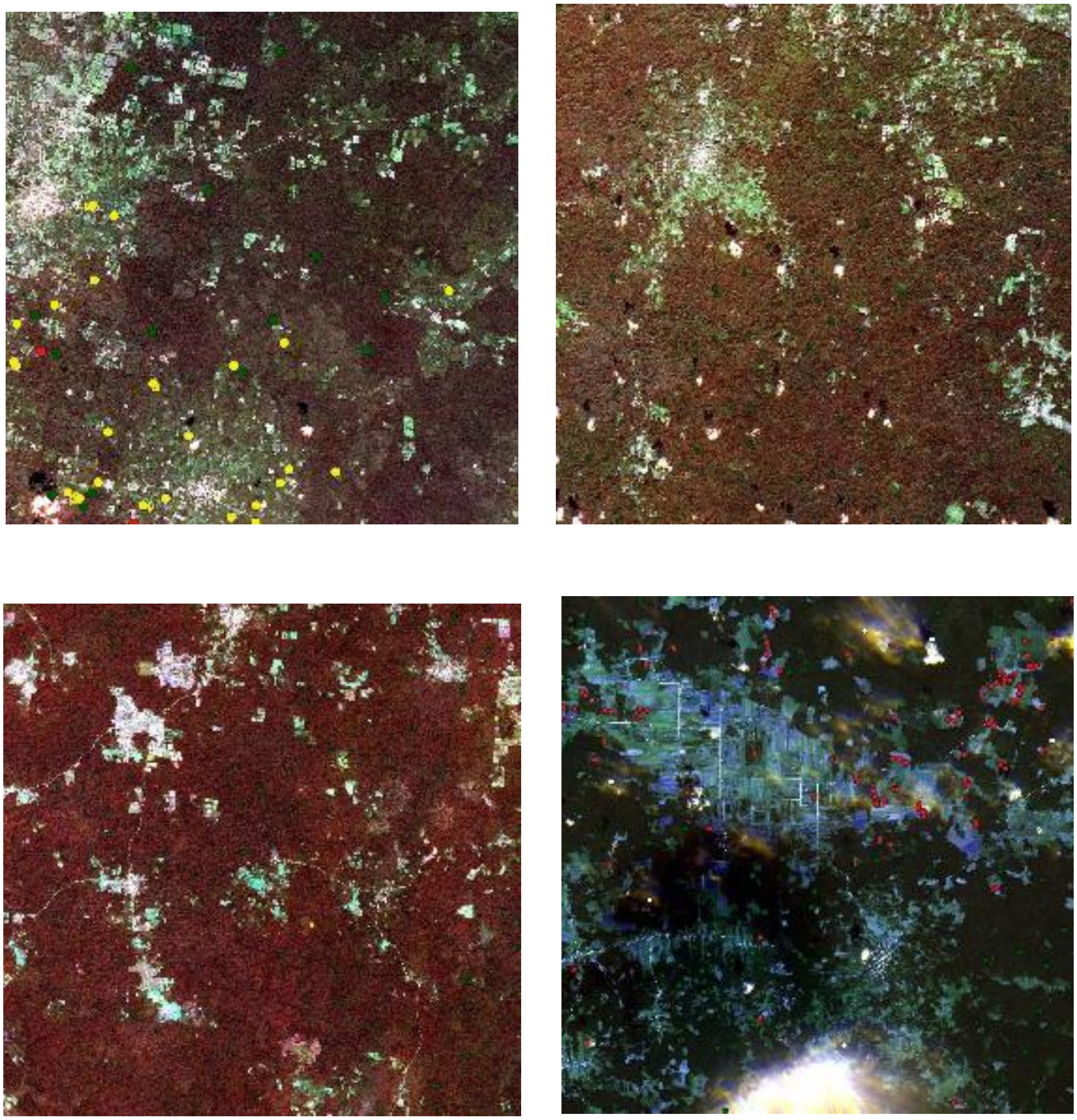


FIGURE 10. DISTRIBUTION OF HIGH-RESOLUTION IMAGES FROM RAPIDEYE FOR THE COLOMBIAN DEMONSTRATION AREA. IMAGES ARE COLOR COMPOSITES, 10-KM WIDE EACH, SUPERIMPOSED OVER THE AGREED FOREST DISTRIBUTION FOR CIRCA 2000 (GREY) AND NON-FOREST (BLACK).

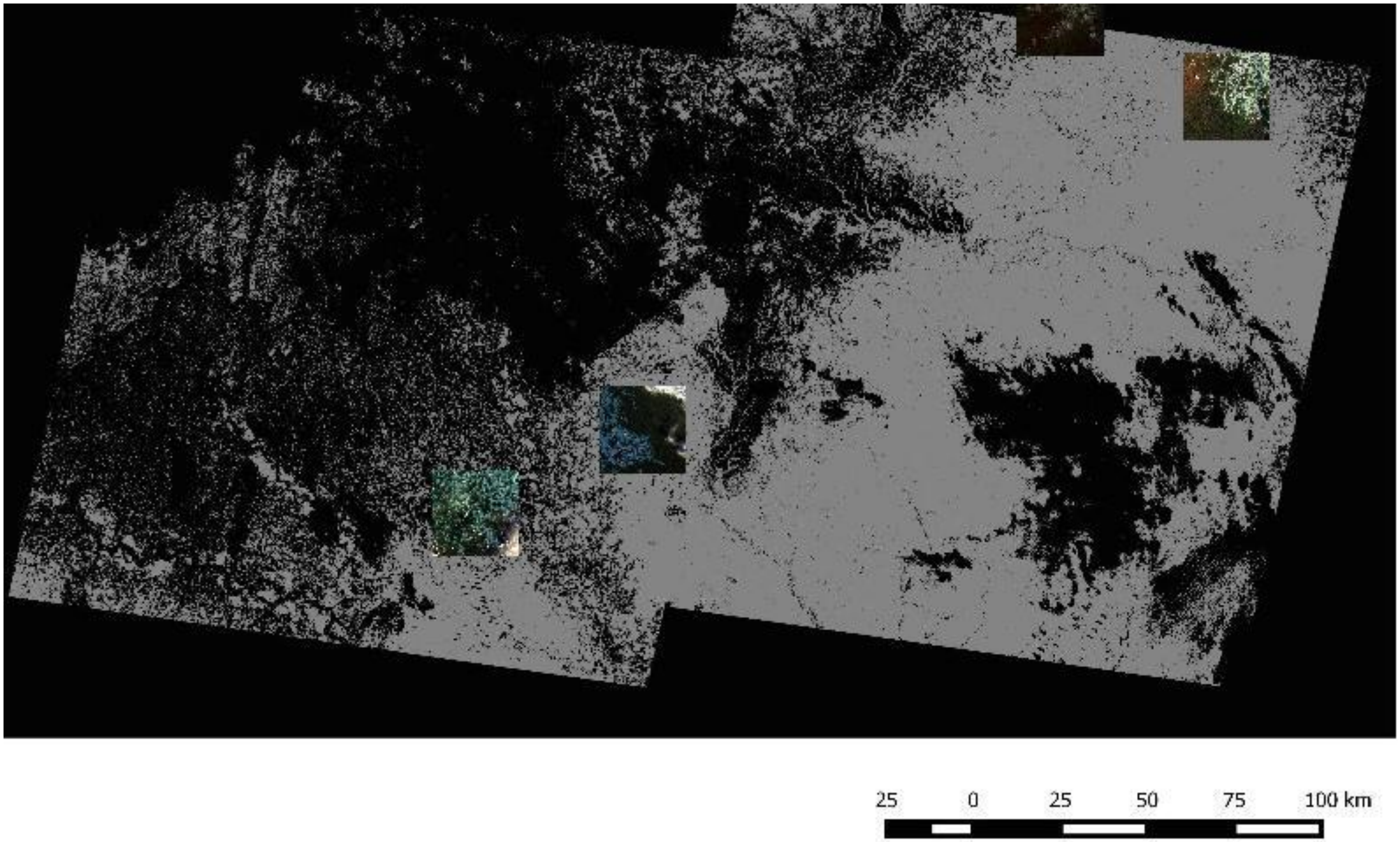


FIGURE 11. DISTRIBUTION OF POINTS OF HIGH-RESOLUTION IMAGES FROM RAPIDEYE VISUALLY INTERPRETED FOR THE MEXICAN DEMONSTRATION AREA. POINTS ARE: GREEN – FOREST, RED – ACTIVE FARMLAND. POINTS ARE SUPERIMPOSED OVER THE AGREED FOREST DISTRIBUTION FOR CIRCA 2000 (GREY) AND NON-FOREST (BLACK).

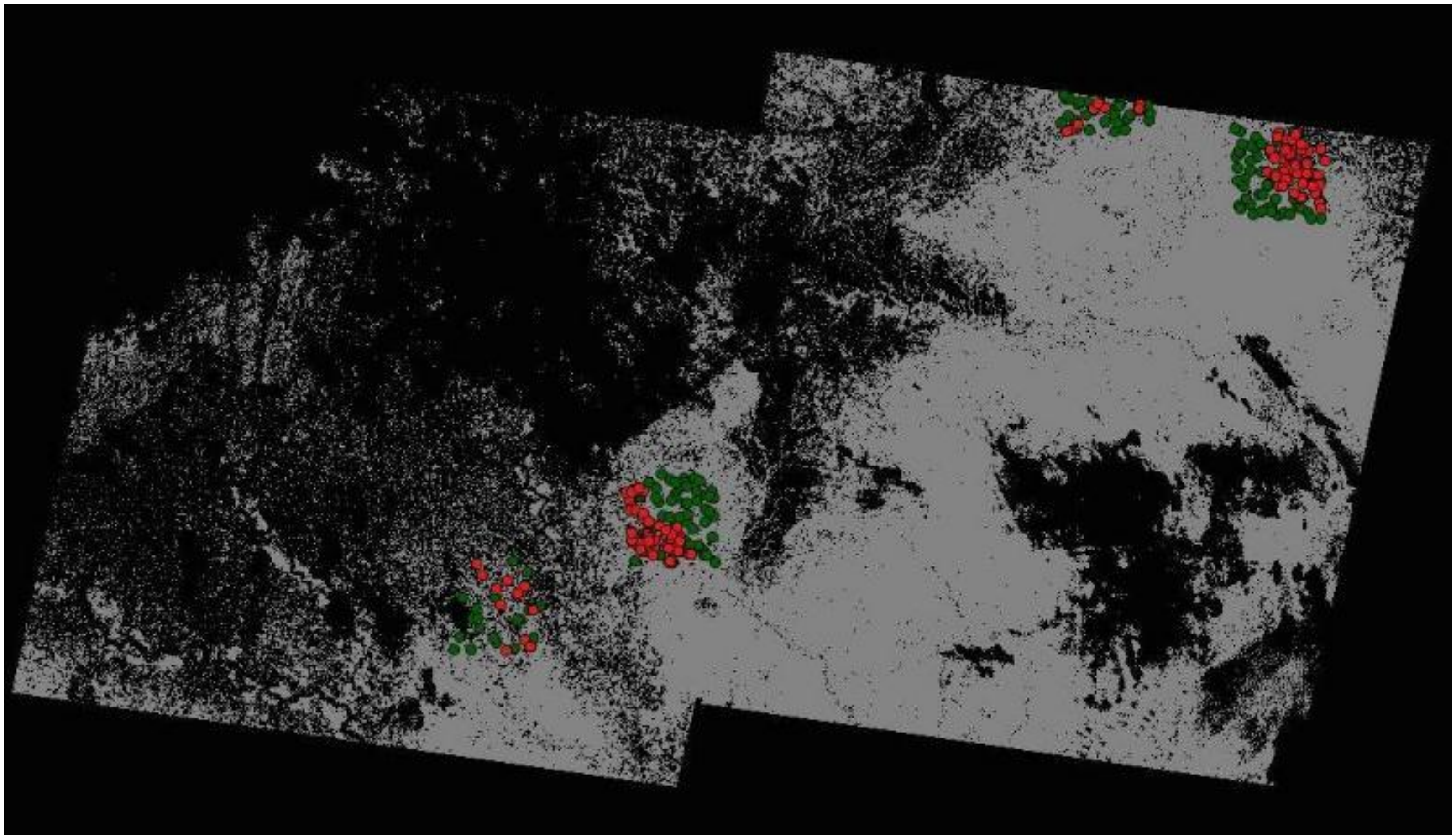
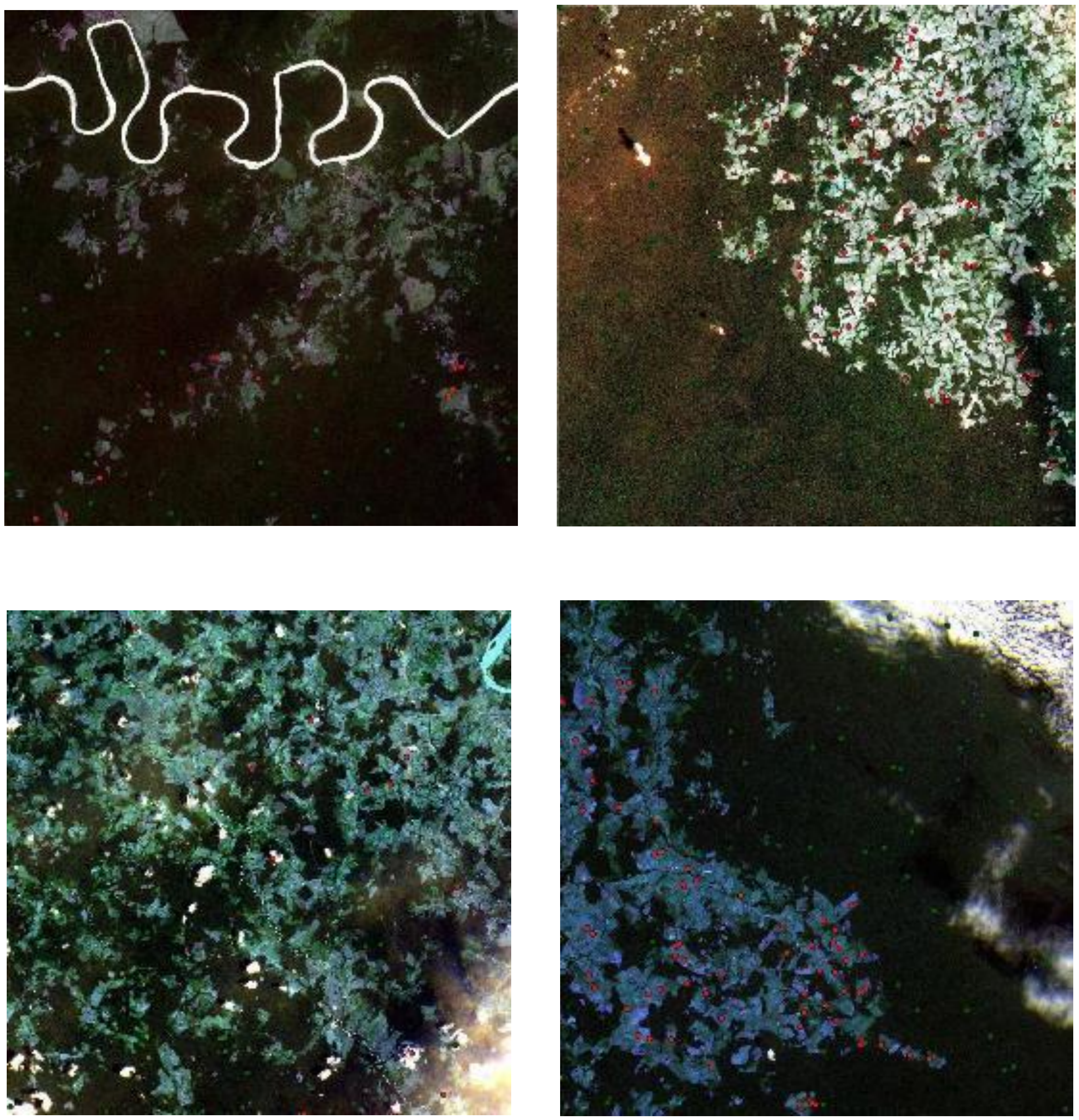


FIGURE 12. HIGH-RESOLUTION IMAGES FROM RAPIDEYE WITH POINTS VISUALLY INTERPRETED FOR THE COLOMBIAN DEMONSTRATION AREA. POINTS ARE: GREEN – FOREST, RED – ACTIVE FARMLAND, YELLOW – SECONDARY FOREST FALLOW.



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