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Monitoring Forest Change in Southeast Asia: Case Studies for USAID

Lowering Emissions in Asia's Forests

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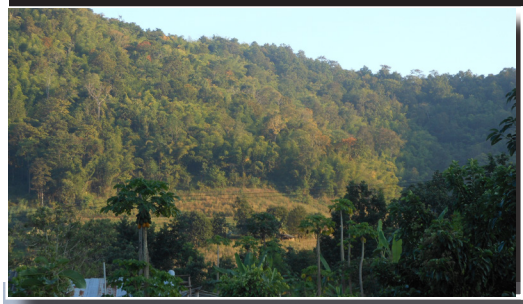

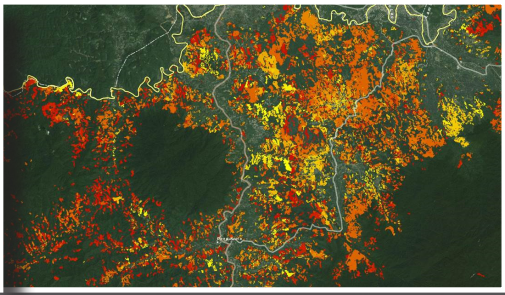

Abstract

Monitoring Asia's changing forests in a consistent, repeatable manner is of great importance to understanding the carbon balance. As part of the United States Agency for International Development (USAID) Lowering Emissions in Asia's Forests (LEAF) program's effort to facilitate the development of practical monitoring systems, this study evaluated three automated forest loss detection algorithms in the four core USAID LEAF study areas using Landsat data spanning 2001 to 2013.

The evaluated algorithms were CLASlite, Hansen's Global Forest Loss product, and a new algorithm called Multiple Linear Trend Analysis (MLTA). Google Earth Engine (GEE) was used throughout this project as an efficient cloud-based computation platform. GEE provides massively parallel computing infrastructure available to many areas with limited information technology infrastructure. CLASlite is freely available, but rather difficult to properly calibrate to the changing forest dynamics of the four study areas. Hansen's loss product is readily available, spatially explicit, and updated annually, but lacks any ability to refine the definition of deforestation. Additionally, it has no separate forest degradation category. MLTA can be customized to meet specific definitions of deforestation and forest degradation but proved difficult to properly calibrate to characterize deforestation and forest degradation without sufficient on-the-ground knowledge.

Results indicate no clear trends of annual forest loss rates throughout the four study areas from 2001 to 2013. Also, there is a large variance in the amount of forest loss detected by each algorithm. A quantitative accuracy assessment was conducted using the Timesync Landsat visualization tool across a total of 2,000 30- by 30-m sample pixels. Results indicate that the Hansen product, while only identifying forest cover loss, overlaps with much of what the accuracy assessment characterized as forest degradation and degradation, thus combining the two in a single class. The CLASlite products generally had the lowest accuracies. The MLTA product had high accuracies in some areas, which indicated that with better calibration the method could potentially meet monitoring needs.

Remote sensing-based methods have the potential to provide practical automated estimates of forest change in Asia. Currently, methods are being actively developed to meet these growing needs. Results from this study indicate that currently available methods may be sufficient for first-order estimates of deforestation and degradation, but further refinement may be necessary for more precise needs.

Keywords

remote sensing, Landsat, Asian forests, REDD+, USAID LEAF, forest loss monitoring, CLASlite, Hansen Global Forest Change, trend analysis

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Background

The USAID/Regional Development Mission for Asia's (RDMA) Lowering Emissions in Asia's Forests (USAID LEAF) project aims to strengthen the capacity of countries in the Asia region to produce meaningful and sustainable reductions in greenhouse gas (GHG) emissions from the forestry-land use sector. To achieve this, USAID LEAF is seeking rapid, robust and cost-effective methods for monitoring deforestation and forest degradation.

Forest degradation is estimated to account for a large portion of forest biomass loss in the region; however, due to its complex spatio-temporal patterns, consistent detection using automated algorithms has proven difficult. Currently, most countries do not have the ability or data to rapidly assess the significance of forest degradation and historical patterns and trends. Recent advances in algorithms that manipulate satellite imagery, combined with cloud-based computational capacity, are providing potential means for countries to develop systems to begin meeting these needs.

In an effort to provide repeatable, statistically valid deforestation and forest degradation estimates, the U.S. Forest Service International Programs (USFS-IP) through the Remote Sensing Applications Center (RSAC), in collaboration with the USAID LEAF project, designed and implemented methods to address three key needs:

- A Landsat-based cloud-free annual and biennial image compositing process for use in CLASlite mapping software;
- A change detection method sensitive to slow-onset, long duration forest cover loss in Southeast Asia and Papua New Guinea;
- A method to validate forest cover change products depicting deforestation and forest degradation from 2001 to 2013.

Figure 1—Location and outline of four USAID LEAF study areas analyzed for this project.

High relief tropical forests pose many challenges for automated, optical remote sensing-based forest change analysis. This is primarily due to clouds/cloud shadows, hillslope shadows, smoke, haze, spectral saturation, and limited archived imagery. In addition to difficulties due to data limitations, forest change patterns are variable and often-times slow to emerge. These difficulties can be further complicated by the need for deforestation and forest degradation estimates to relate land cover change to land use change. Since land use definitions vary greatly between regions/countries, only forest land cover change was addressed in this study.

For this project, RSAC developed and implemented techniques within Google Earth Engine (GEE) that enable the entire Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM)+, and Operational Land Imager (OLI) archive to be leveraged to provide cloud- and cloud-shadow-free pixels for analysis.

Landsat-based annual/biennial image composites use the cloud/cloud-shadow-free pixels to depict forest cover status throughout the analysis period. These data were used in two separate change detection approaches, including CLASlite, as well as an independent image interpretation-based method known as TimeSync (Cohen et al. 2010). These methods were applied across the four core USAID LEAF study areas (figure 1):

- Madang Province, Papua New Guinea
- Houaphan Province, Laos
- Lam Dong Province, Vietnam
- Mae Sa-Kog Ma UNESCO Man and Biosphere Reserve (MAB), Thailand

Each of the study areas presents different types and frequencies of deforestation and forest degradation. It was expected that Madang Province and Houaphan Province would exhibit forest cover change largely resulting from shifting agriculture, while Lam Dong would exhibit forest cover change due to long-term land use change from forest to large-scale agriculture. Because the Mae Sa-Kog Ma MAB study area is mostly within a preserved area, it was expected to undergo very little forest change.

Methods

Computing Environment

All analyses for this project were conducted using Landsat data. Until recently, using Landsat data required time-consuming image downloading and pre-processing, such as cloud removal. Since about 2010, Google has been constructing a cloud-based geospatial data computing system called Google Earth Engine (GEE). As of 2015, GEE is still in a beta testing phase, but provides extensive capabilities. GEE provides access to most freely available geospatial raster data sources including approximately two million Landsat scenes (Gorelick 2013). In addition to eliminating data acquisition time, all computation is performed in parallel over many small image tiles, reducing processing times by orders of magnitude. Since remote sensing in the tropics requires an extensive amount of data and computation, GEE was the chosen primary computing method.

The Landsat archive provides an extensive record of earth surface conditions across the globe spanning about 40 years. These data vary in availability and quality across space and time and therefore require careful preparation to provide the best possible depiction of earth's surface conditions and dynamics.

Our first objective was to create Landsat-based cloud-free annual or biennial composites for each study area to be used with the CLASlite algorithm. This required the six common optical bands of Landsat.In order to reduce the impacts of seasonality, the first half of the dry season was the targeted period. In Madang, this was from the 28th of May to the 3rd of October. The targeted date range in the remaining study areas was the 1st of November to the 31st of January. Image availability and quality proved significantly more limited in Madang Province, PNG. Therefore, a two-year window for each composite was developed in order to obtain a reasonable proportion of observations of sufficient quality.

A common difficulty with optical remote sensing data is cloud and cloud-shadow removal. Google has created a simple cloud-masking algorithm based on the spectral and thermal properties of clouds. It finds pixels that are bright and cold, but do not share the spectral properties of snow. Specifically, it defines the cloud score as the minimum of the following values:

((blue band - 0.1) / 0.3) - 0.1,

((blue band + green band + red band - 0.2) / 0.8) - 0.2,

((NIR band + SWIR1 band + SWIR2 band - 0.3) / 0.8) - 0.3,

((300 - temp band) / 290) - 300, and

((0.8 - ((green band - SWIR1 band) / (green band + SWIR1 band))) /0.6) - 0.8 (http://earthengine.google.org/).

Through extensive testing and qualitative analysis, it appears to work well in all areas except for where cirrus clouds overlap with perennial snow cover. This was not of concern in the USAID LEAF study areas.

Since cloud shadows share similar spectral properties with water and hill-slope shadows, they are more difficult to identify using simple rule sets than clouds. Where sufficient Landsat data were available, a newly developed cloud shadow masking method was used. The Temporal Dark Outlier Mask (TDOM) algorithm identifies pixels that are dark in the infrared bands but are found to not always be dark in past and/or future observations. This is done by finding statistical outliers with respect to the sum of the infrared bands. Since this method requires a sufficient number of observations (~4 or more), it could not be implemented in Madang Province. As a result, all pixels that were dark in the infrared bands were masked in Madang Province. TDOM was implemented in all other USAID LEAF study areas.

After cloud/cloud-shadow masking, the remaining values must be summarized to develop a composite image. Several common compositing methods were qualitatively evaluated (see box 1). Ultimately the Median summary method was chosen. While the median value of cloud/cloud-shadow-free pixels may not include pixel values from the same date across different bands and may omit pixels that include forest loss, it tends to be the least prone to include any noise or artifact.

Deforestation/Forest Degradation Detection Methods

Change Detection Methods Overview

Once the task of choosing the best image compositing method was completed, the primary focus of this study was to identify methods for automated monitoring of deforestation and forest degradation. Three methods were tested (table 1):

- **CLASlite** (Asner et al. 2009) is a method that is easily implemented, is freely available, and has proven effective at identifying deforestation and forest degradation in the tropics. It has three primary steps: data preparation, fractional cover analysis, and change classification. The data preparation methods were not used since cloud/cloud-shadow-free composites were provided from GEE. The fractional cover analysis method uses an extensive spectral endmember library to decompose the percent photosynthetic, non-photosynthetic, and bare ground found within each pixel. The three bands of fractional cover are then used in a hard-coded change detection decision set to find deforestation and disturbance (an approximation of forest degradation).

Box 1—Compositing Methods Tested

Four compositing methods were tested for this study. They included:

Optimal date-centered method—Cloud/cloud-shadow-free pixels were chosen by their proximity to a specified date.

- Pros:
  - Ensures that for each pixel, values across all bands are from a single date
  - Theoretically minimizes phenology impacts
- Con:
  - Because clouds/cloud-shadows missed in the masking step can easily be selected, outputs tend to appear noisy

Percentile-stretch summary method—In order to avoid omitting changed pixels across a long compositing period, pixels are chosen using different percentiles. Bands correlated to the presence of vegetation (green and near-infrared) were summarized using a lower percentile reducer, while bands correlated to the absence of vegetation (red, and short-wave-infrareds) were summarized using a higher percentile reducer.

- Pro:
  - Increases the likelihood of including pixels that underwent forest loss
  - Increases the likelihood of including cloud/cloud-shadow artifacts missed in the filtering process
- Con:
  - Pixel values may be from different dates across different bands

Percentile vegetation index method—In order to try to ensure the values across the different bands for a given pixel were from the same observation and corresponded to some level of vegetation, a percentile vegetation index method was tested. This method involved finding the pixels that corresponded with the nth percentile of a given vegetation index.

- Pro:
  - This method provides pixel values across all bands from single dates
- Con:
  - Heightened vegetation index values can correspond with omitted clouds/cloud-shadows, reducing the composite's quality

Median summary method—While the median value of all cloud/cloud-shadow-free pixels may not include pixel values from the same date across different bands and may omit pixels that include forest loss, it tends to be the least prone to include any noise or artifact.

- Pro:
  - Least likely to include cloud/cloud-shadow artifacts missed in the filtering process
- Con:
  - Values across different bands may be from different date

- **Hansen Global Forest Change** (Hansen et al. 2013) is a pre-computed global forest change product that depicts forest loss and gain from 2000 onward. It is updated annually and freely available. It uses various spectral indicators of the vegetated states in a statistical model to detect deforestation. The product has come under some criticism that it does not depict forest degradation adequately. Despite this limitation, it is likely to be a good product for detecting deforestation since its final loss detection methods are based on statistical models instead of hard-coded heuristics.

- **Multiple linear trend analysis (MLTA)** was developed in an effort to design a change algorithm that is sensitive to much of the slow forest change that Hansen is cited for omitting. The method builds on the work of Vogelman et al. (2012), Forest Monitoring for Action (FORMA) (Hammer et al. 2009), and the Real Time Forest Disturbance Trend Disturbance Detection (RTFD TDD) product (http://foresthealth.fs.usda.gov/portal/Flex/FDM?dL=0). Separate deforestation and forest degradation products are produced. It is likely less sensitive to sudden change with a quick recovery than are CLASlite or the Hansen Global Forest Change products.

Table 1—Highlights of the differences of each method

Method name	Primary data source	Preliminary change detection method	Final change detection method
CLASlite	Landsat 5, 7, and 8	Spectral end-member analysis	Multi-year heuristic
Hansen Global Forest Change	Landsat 7 and 8 (as of 2015)	Various change co-variates	Statistical classification model
Multi-date Trend Analysis	Landsat 5, 7, and 8	Moving window FORMA linear trend fit	Multi-date and multi-year heuristic

Moving Window Trend Analysis Method Summary

While the Hansen and CLASlite products both provided potential methods for deforestation and/or forest degradation monitoring, a customized method was developed to leverage theoretical strengths of trend-based forest change detection methods. The moving window trend analysis method is built around the idea that much of the change in the tropics occurs over a period of 2 years or more. For the purpose of this study, this is considered a slow-onset forest disturbance. Since these changes generally have a low magnitude of change over any single year, many algorithms designed to detect abrupt changes will omit them. This algorithm loosely defines deforestation as a severe forest cover change that occurs over the course of 1–3 years. Forest degradation is loosely defined as a subtle forest cover decline that occurs over the course of 3–5 years. Since subtle changes that only occur for a short period manifest the same as noise, they are considered undetectable.

With these definitions in mind, the algorithm first gathers all cloud and cloud-shadow-free Landsat observations within the study years (2000–2014 for this project) for a defined set of date periods using the same cloud masking algorithm and the basic cloud-shadow masking algorithm used to create Landsat composites. The date period is generally between 32 and 64 days, depending on the expected frequency of cloud-free observations in the study area and the phenology of the forest. For each date period, a stack of annual median vegetation index composites is computed. Then, for a specified epoch length, a linear fit is performed using the FORMA linear fit algorithm on a moving window. For example, if the study years are 2000–2014 and the epoch length is 4 years, the first window will be 1997–2000, then 1998–2001, 1999–2002, etc. Each of these epochs will have a slope returned from the FORMA linear fit algorithm (Hammer et al. 2009), resulting in a stack of trends for each pixel for each date period.

The next step is to simplify the series of linear slope stacks. Detectability of change is generally a function of the magnitude of change and how many times it is observed. Vogelmann et al. (2012) used a t-test with respect to the slope of the linear fit to filter real change from likely noise. MLTA adapts this idea of change magnitude and persistence by filtering slopes by the number of date periods the slope is below a certain threshold. If a slope is highly negative in 2 out of 3 of the date periods, it is more likely to be real change than if it only appears negative in 1 of the date periods. Additionally, if the slope is only moderately negative, but appears moderately negative in 3 out of 3 date periods, it is more likely to be real as well. Individual change years are identified using this idea. This results in a stack of binary change/no-change layers.

The final filter is a moving window majority filter. It is expected that deforestation may occur over a shorter period of time, but have a higher magnitude, while degradation will have a lower magnitude, but be observable over multiple epochs. With this idea, a moving majority filter helps to identify persisting subtle trends associated with degradation.

This can yield a depiction of subtle but persistent change, as well as severe, and only moderately persistent change, thus providing a potential alternative method for monitoring deforestation and forest degradation in the USAID LEAF study areas.

Independent Estimation and Validation Methods

Sample Design

In order to compare the products, a total of 2,000 30 by 30-m pixels were sampled and visually interpreted using the TimeSync data analysis tool. A proportional random sample by country area was used to generate these 2,000 samples. This design provides a more precise estimate of omission of forest cover loss than of commission since forest cover loss occurs over relatively small areas as compared to areas of no loss. TimeSync uses Landsat imagery as the interpretive base along with some higher resolution imagery from Google Earth.

Interpretation Method

The TimeSync data analysis tool was used to better understand the validity of the three change detection methods. TimeSync is a tool that can be used for image time series visualization, algorithm calibration, and/or data collection. TimeSync allows for human interpretation of pixel level changes through a time series using the comprehensive coverage provided by the Landsat program (Cohen et al. 2010).

The primary difference between TimeSync and the FAO Collect Earth tool (http://openforis.org/) is that Timesync is oriented around exploiting the strengths of the Landsat archive, with a loose integration of Google Earth. At the time of writing this report, Collect Earth's ability to visualize the rather complex nature of Landsat data was in its infancy compared to TimeSync. For this reason, TimeSync was chosen for this project.

While an ideal independent validation would be based on observations of data not used in the automated analysis, there is no more consistently available set of spatially relevant earth surface observations than the Landsat archive. For this reason, TimeSync primarily relies on the Landsat archive, but incorporates the strengths an analyst can provide by analyzing the Landsat data along with any data available in Google Earth to better understand the change dynamics.

There are four components to TimeSync: an image chip window, a graph window, a data collection form, and Google Earth. When plots are loaded, the image chip window and graph window are opened with data concerning the plot (figure 2). The image chip window shows a Landsat false-color composite for each image found in the time series, highlighting the pixel from the sample. The graph window shows multiple indices with corresponding data that are valuable for the analysis, tracking the pixel through time. The data collection window has multiple fields available for interpreter input based on the specified response design.

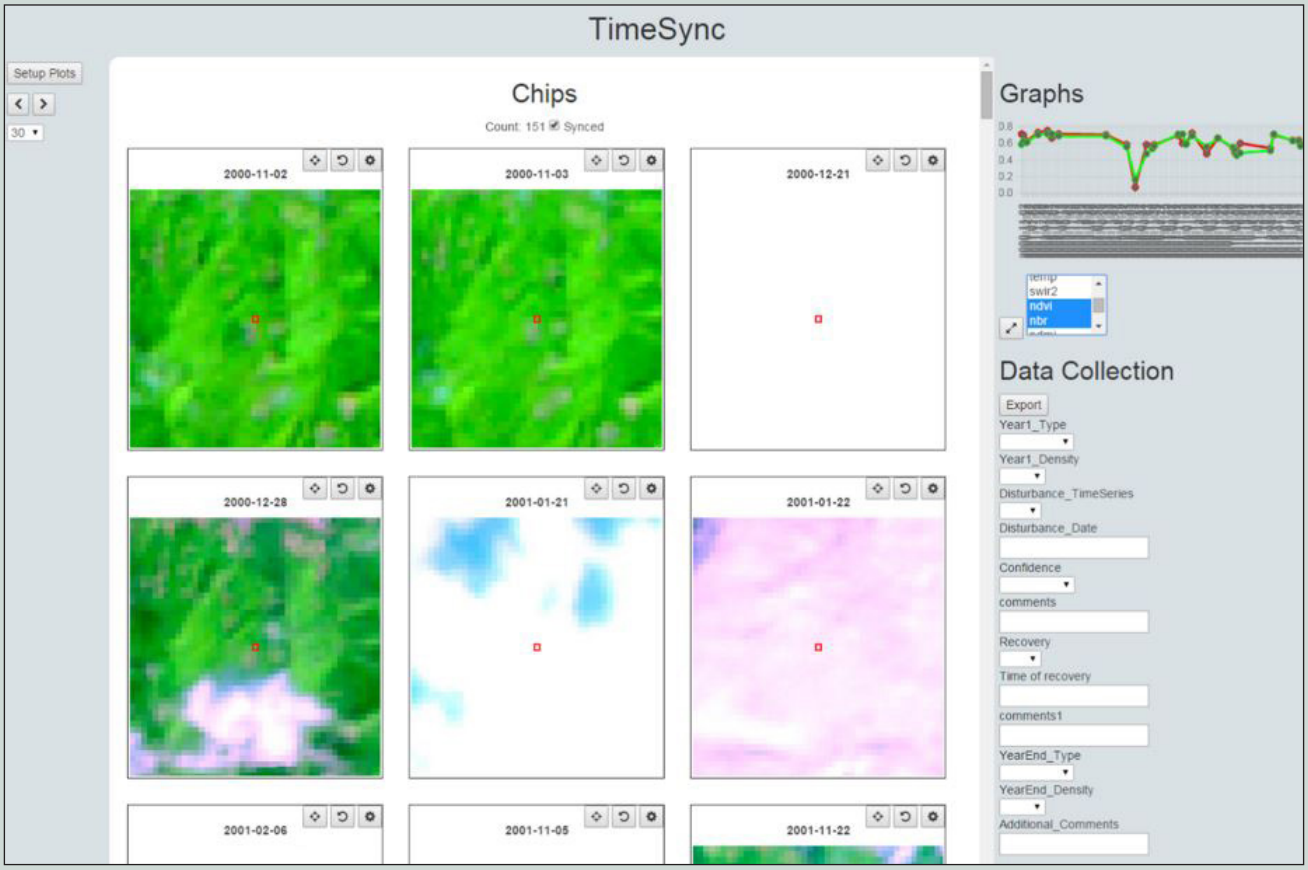


Figure 2—Example of the GEE-based Timesync interface used for this study. Additionally, Google Earth was used as a source of high resolution imagery when available.

Response Design

The response design was intended to depict attributes of forest cover change found in all three products, as well as forest cover loss characteristics related to forest degradation. Each sample site is a single Landsat pixel. The user must classify the site as forest or non-forest using the data from the first available observation within the analysis period. A forested area was defined as having more than 25 percent tree coverage with a height above 5 meters, as also defined in Hansen's Global Forest Change Product (Hansen et al. 2013). Plots were also classified as a high or low density forest. A high density forest had approximately 80-100 percent forest cover of the site, while a low density forest was determined to be approximately 25-80 percent forest cover. While such a specific set of criteria is difficult to interpret using Landsat data alone, a combination of color and texture in the Landsat data, any available high resolution data in Google Earth, and various Landsat-based vegetation indices were all used to enhance the ability of the interpreter to properly classify the plots. Additional components of the response design included data about disturbance occurrence, disturbance date, user confidence, recovery occurrence, recovery date, end forest type, and end forest density with multiple fields for comments.

Results

Landsat Cloud-Free Composites

Creating consistent wall-to-wall annual cloud-free composites proved to be challenging for all of the study areas. The TDOM cloud-shadow masking algorithm was not used in Madang Province due to the limited Landsat data record. Landsat 5 TM data generally serve as a primary Landsat data source from the beginning of the analysis period to 2012, but there were no Landsat 5 TM data available over Madang Province. In addition, most of the available Landsat 7 ETM+ data was plagued with missing data lines due to a hardware malfunction on the sensor. These two compounding issues resulted in an insufficient number of pixels to identify dark outliers. Instead, all dark pixels in the infrared bands were masked. While this did include some hill shadow areas, due to the relatively high sun angles found at lower latitudes, very few areas were committed in the cloud shadow mask. Despite including a date period of 128 days over a two-year span for each composite, many composites still had many areas without high quality observations to use. Many pixels only had a single available Landsat observation, increasing the likelihood of including a pixel value that was a seasonal outlier, thus introducing increased seasonal variation across the composites. All of these factors combined led to composites that were often only of moderate quality.

The Landsat archive was relatively robust in the remaining three study areas. Because sufficient imagery was available to find dark outliers, the TDOM cloud-shadow-masking algorithm was used in Houaphan, Lam Dong, and Mae Sa-Kog Ma MAB. The primary difficulty in these study areas was the presence of haze and some smoke. Haze proved difficult to consistently mask due to its highly variable optical depth and similar spectral properties to many bright surfaces. Since most change detection algorithms utilize the higher signal-to-noise ratio of longer wavelength bands, it was expected that haze would provide limited impact to the detectability of forest loss. Despite the relatively greater availability of Landsat imagery in these three study areas, there were still many areas during some years that lacked wall-to-wall coverage (figure 3).

Composites were created by using the median summary method (see box 1). This method was chosen after extensive qualitative comparisons of different outputs. While cloud/cloud-shadow masking eliminates much of the noise in the data, many artifacts are likely omitted in the masks. Since artifacts are likely to be outliers, using the median value reduces the likelihood of including them.

Figure 3 shows a high and low quality resulting composite for the Houaphan study area.

Qualitative Overview

Since forest loss is generally assumed to be detectable one or two years after the start of the event, there is some expected deviation between when each algorithm indicated there was forest loss. For the purpose of this study, the final result for all forest loss algorithms was the first year of detectable forest loss. The five final forest change year outputs were (figure 4):

- Hansen forest loss year 2014 (Does not explicitly exclude or include forest degradation)
- CLASlite deforestation
- CLASlite disturbance (implicitly degradation)
- Multi linear trend analysis (MLTA) deforestation
- MLTA degradation

Some general patterns emerged between the products across all study areas. In general:

- The Hansen product provided what appeared to be a low-noise, somewhat conservative estimate of forest loss.
- The CLASlite deforestation and disturbance products appeared to be somewhat noisy and inconsistent relative to the other products.
- The MLTA deforestation product followed the same general spatio-temporal patterns of the Hansen product, but was less conservative.

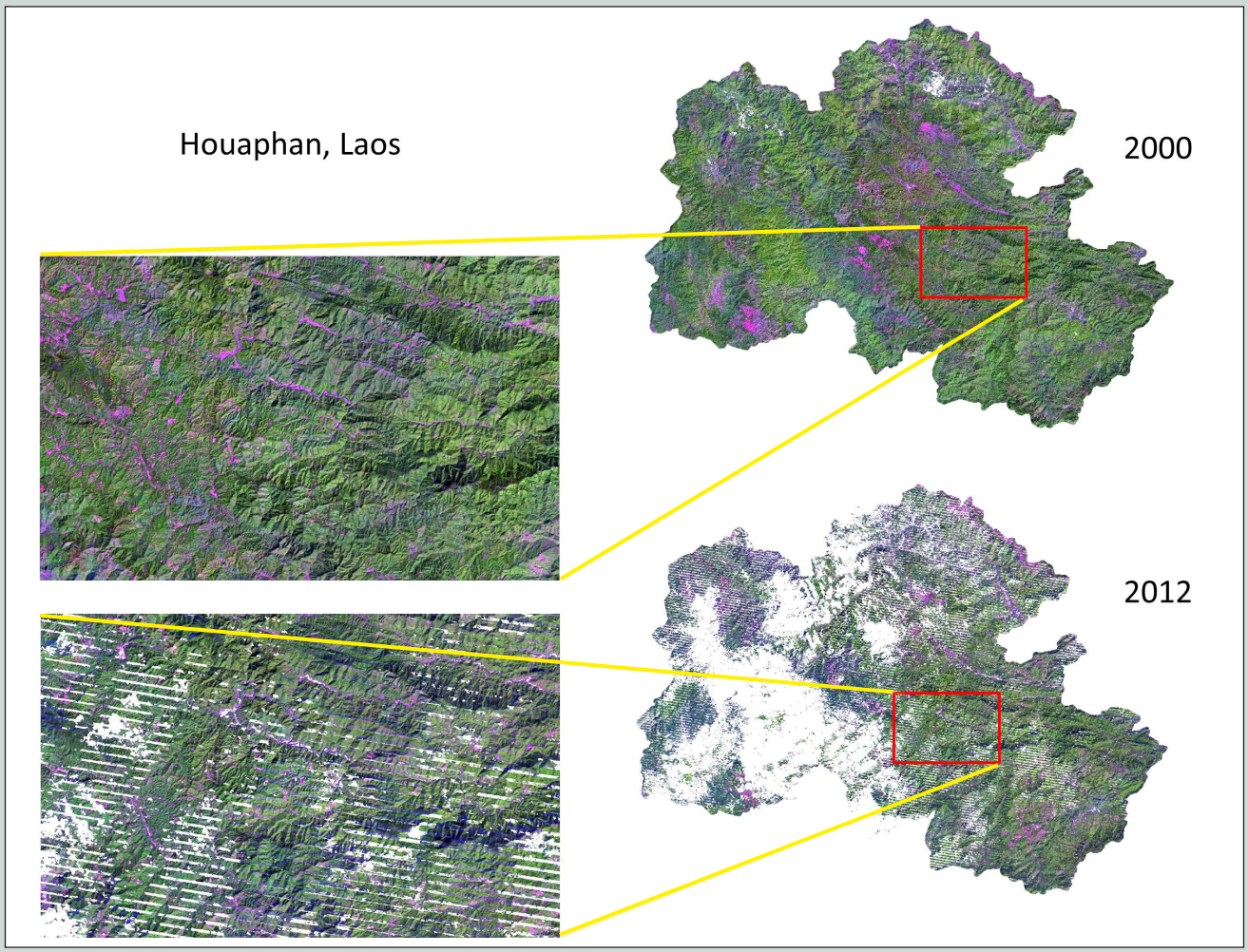


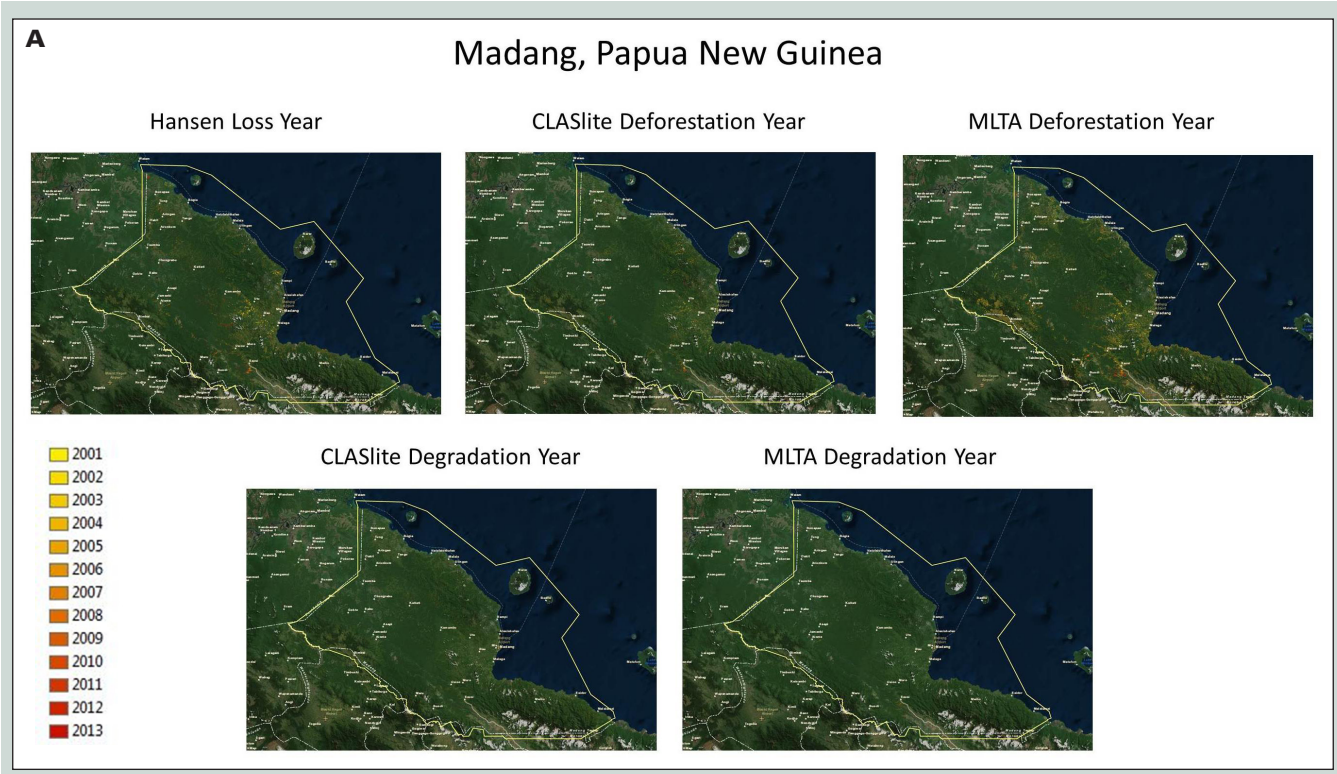
Figure 3—Example of composites from Houaphan Province, Laos. The top set of images depicts a best-case-scenario for a composite, while the lower image represents a worse-case-scenario. White areas represent areas without high quality observations available. Missing data due to cloud/cloud-shadows as well as the more linear Landsat 7 ETM+ scanline correction anomalies are evident.

- The MLTA degradation product provided a conservative estimate of forest degradation.
- The MLTA deforestation product may have included degraded areas that should have been included in the degradation product instead.

All forest loss products detected limited change in Madang (figure 4a and 5a). The areas that were detected varied in consistency between products. Given the paucity of the Landsat data record, it was expected that the outputs would be variable depending on how the algorithms handled null data values.

Beyond the frequency of change, more universal patterns emerged between the three products across all study areas.

- Generally, Hansen found areas in similar locations as MLTA deforestation, but to a lesser extent (evident in the expanded example regions in figure 4).
- Both CLASlite and MLTA products detected limited degradation.
- Generally, the CLASlite degradation product depicted areas that were greater in spatial extent and made sense with respect to the CLASlite deforestation product (figure 5 b and c).
- CLASlite outputs generally included more Landsat 7 ETM+ scanline correction anomalies than the other products (figure 5c).
- While both CLASlite and MLTA used the exact same data source, the final change algorithms clearly provide varying levels of sensitivity to the frequency of available observations.
- Additional anomalous results from CLASlite are evident in the MAE Sa-Kog Ma MAB CLASlite Deforestation Year product (figure 4d). Here, change rates were much higher than the Hansen Loss Year or MLTA Deforestation Year products. This is especially surprising since this area is largely within a reserve.


A
Madang, Papua New Guinea
Hansen Loss Year
CLASlite Deforestation Year
MLTA Deforestation Year
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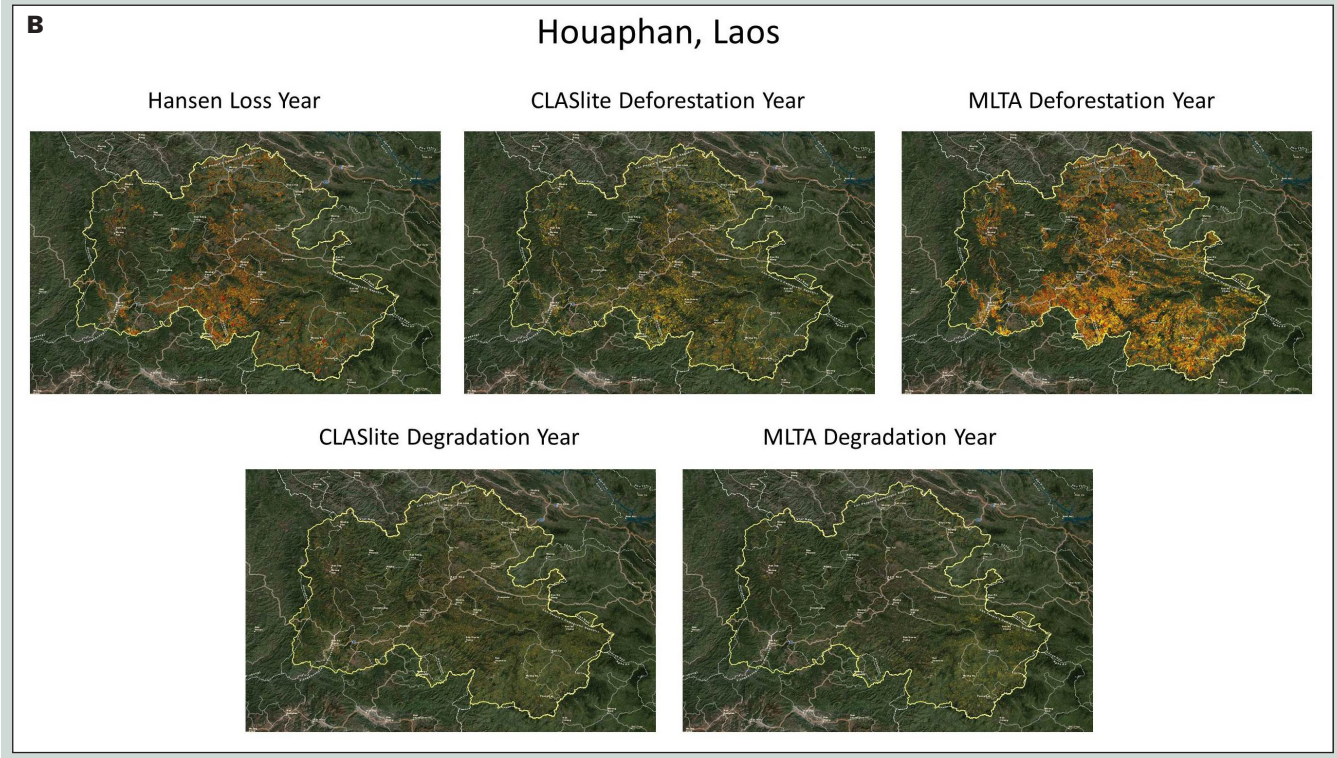
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Hansen Loss Year
CLASlite Deforestation Year
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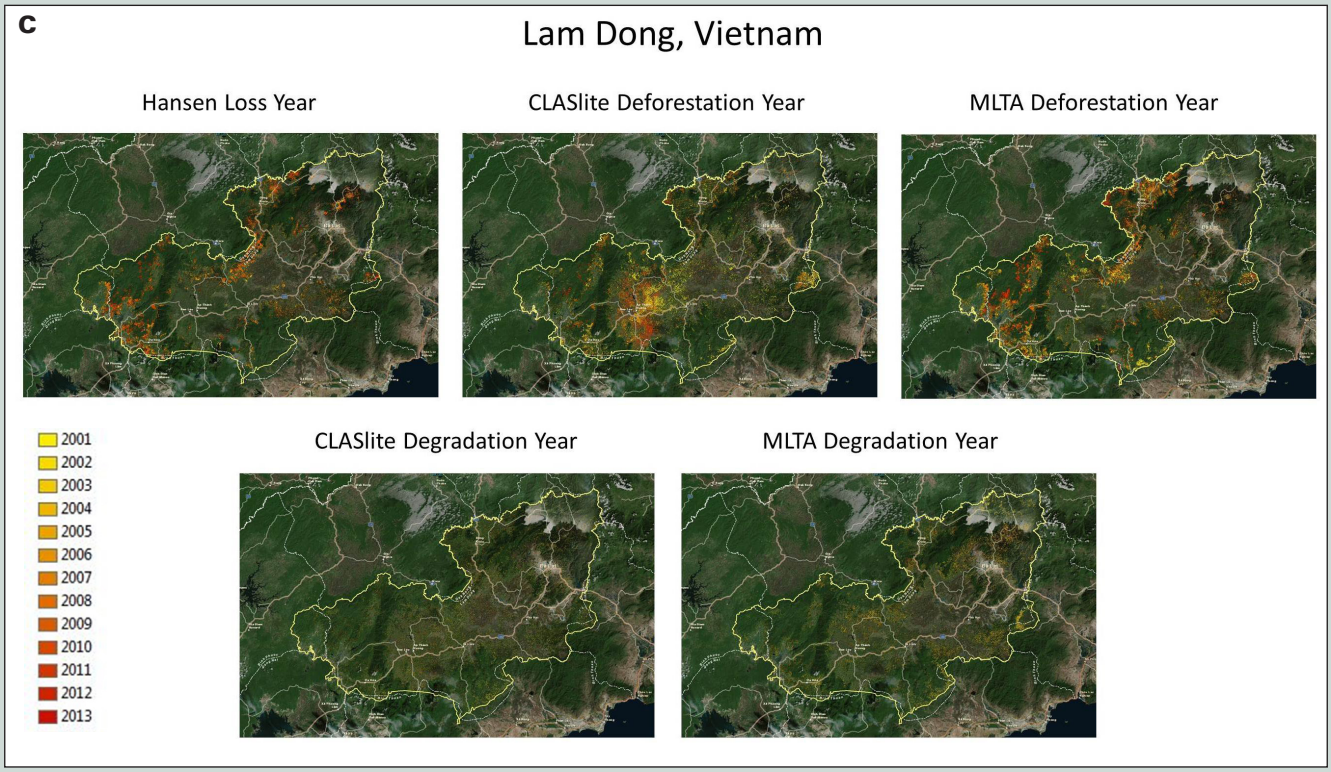
MLTA Degradation Year



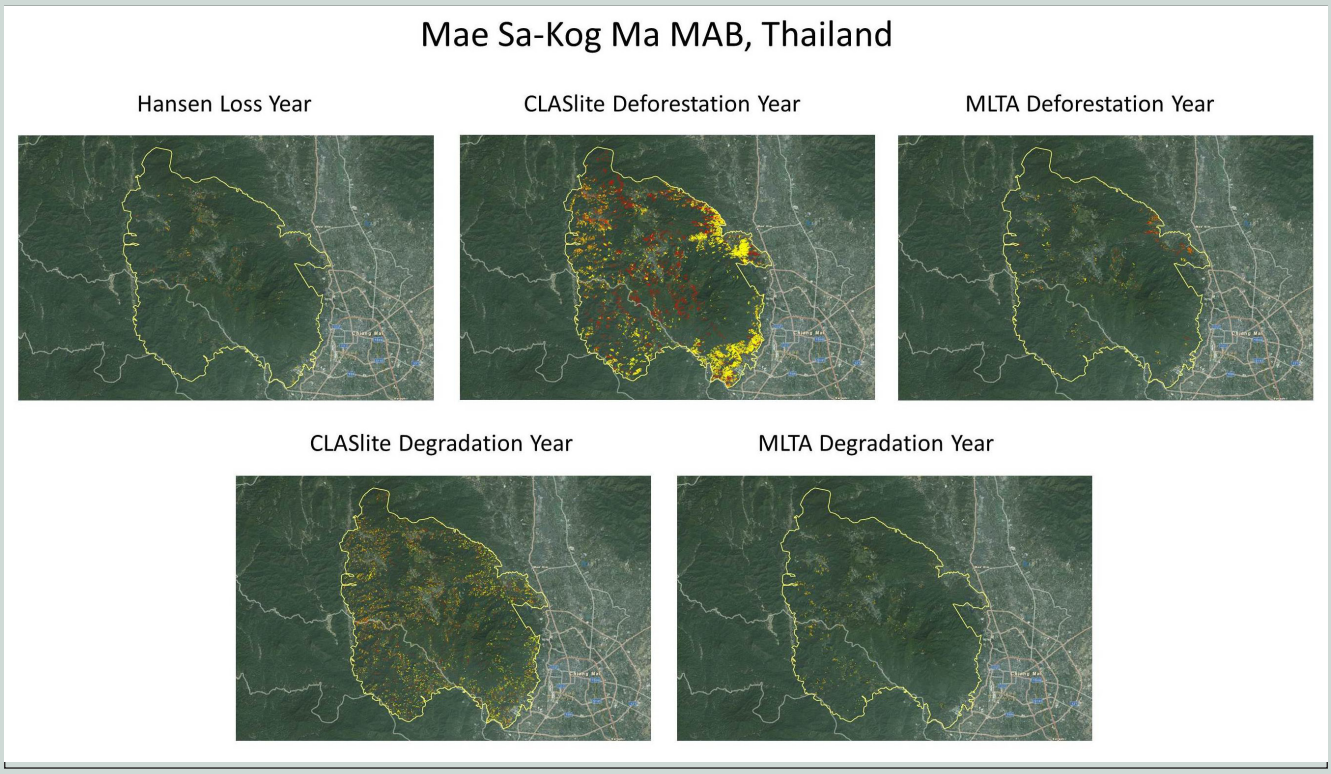
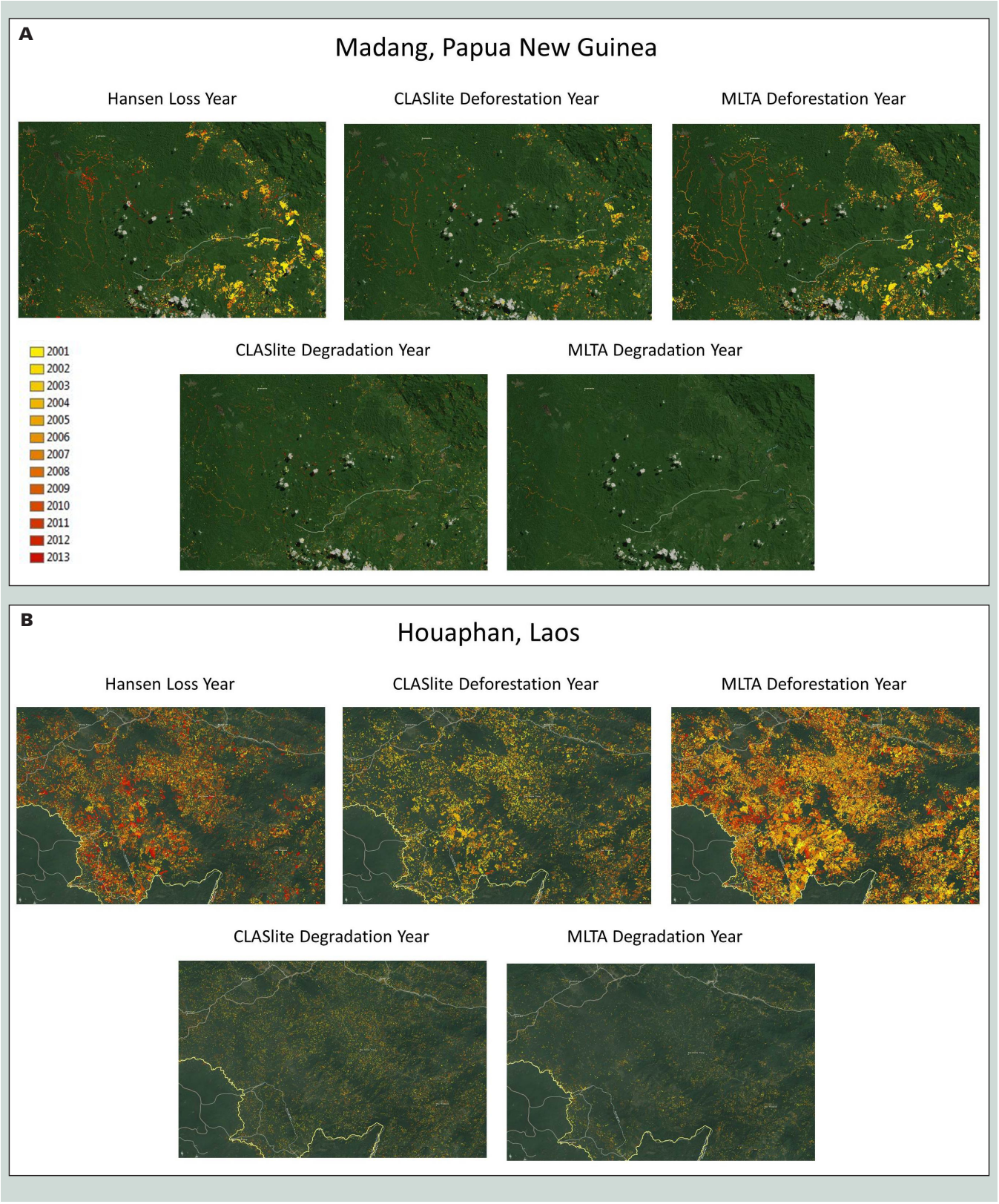


Figure 4—Sub-figures A through D show a general overview of individual study area-wide deforestation and degradation outputs. At this scale, very little forest loss is evident in most study areas. Some of the broader patterns of agreement between MLTA Deforestation Year and Hansen Loss Year can be seen in *(B and C)* Houaphan and Lam Dong. Also of note is the anomalous nature of the CLASlite Deforestation Year output in *(D)* Mae Sa-Kog Ma MAB.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CLASlite Deforestation Year
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MLTA Degradation Year

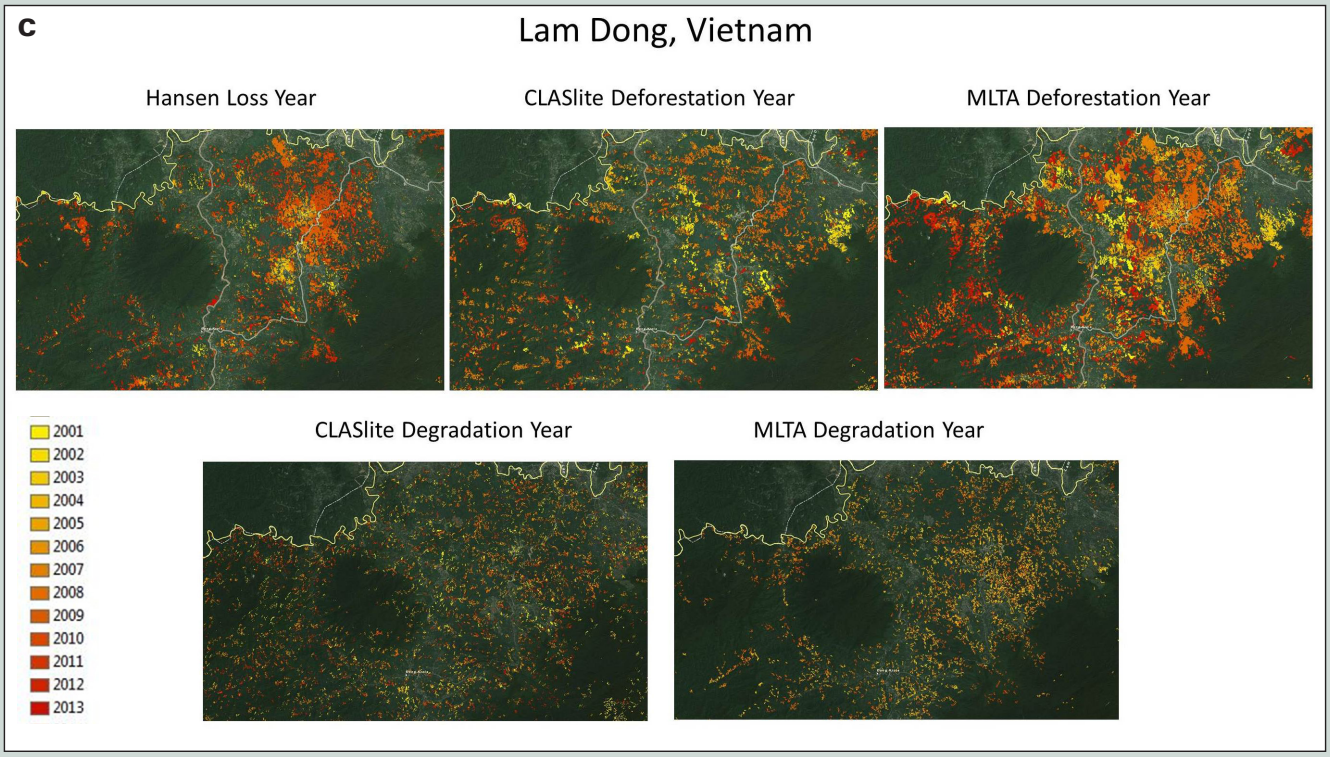


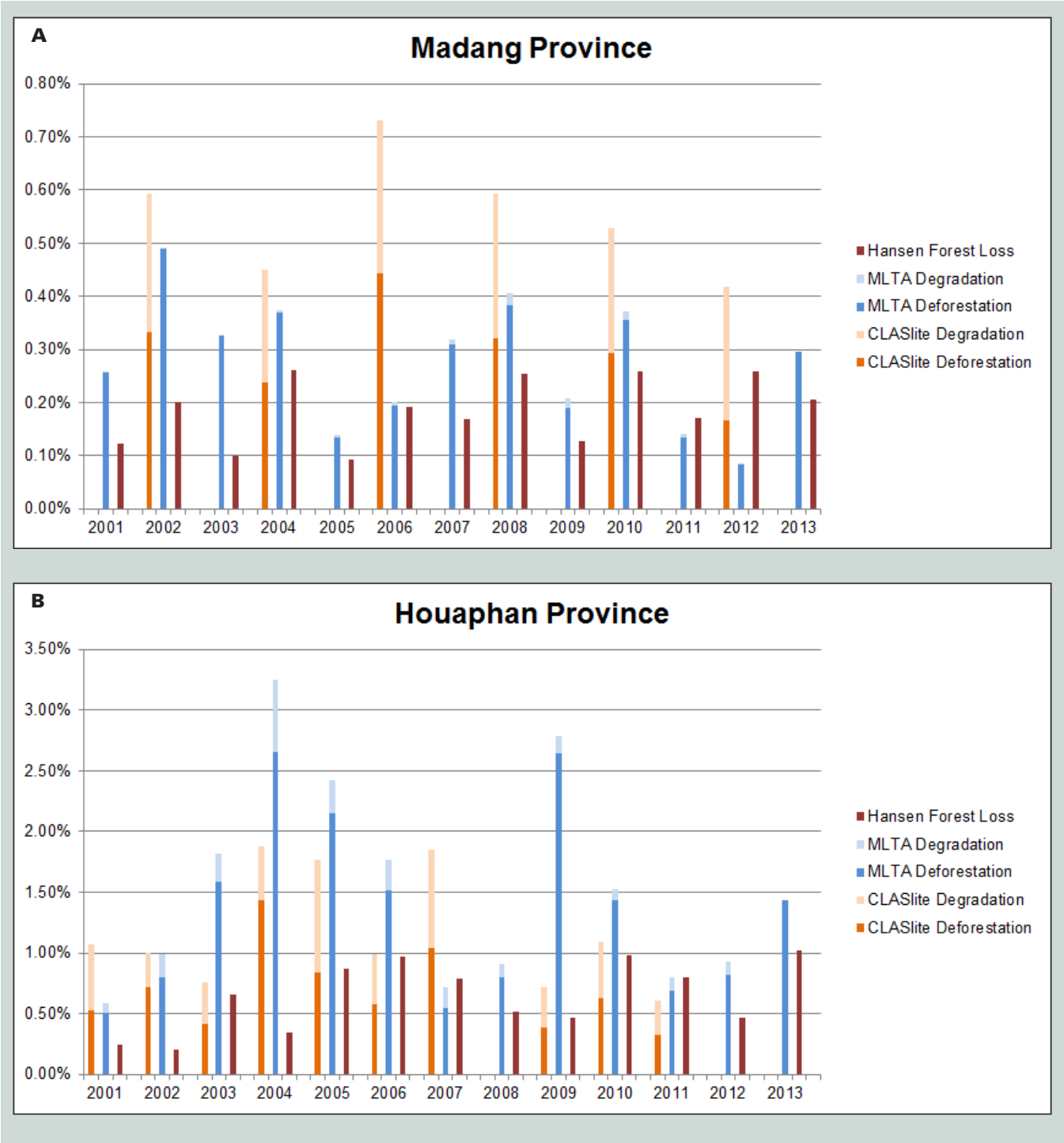
Figure 5—A through C shows more detailed examples from three of the study areas (Thailand was not shown again since it was already shown at detailed scale in Figure 4D). It is evident that the spatio-temporal patterns of the Hansen Loss Year and MLTA Deforestation Year products are somewhat similar in these three study areas, while the CLASlite Deforestation Year product shares limited areal coverage and generally detects change as occurring during different time periods. Both degradation products detected limited change, with the MLTA Degradation Year product providing the most conservative depiction.

Forest Loss Dynamics Results

In addition to visually comparing the products across the study areas, we also wanted to gain a sense of the dynamics of the rate of deforestation and forest degradation during the analysis period between the study areas. Since many of the differences among the forest loss rates can be confounded by a number of variables (data anomalies, algorithms, etc.), gaining a concise understanding of the broader temporal trends of forest loss proved challenging.

Nevertheless, in order to visualize annual change rates across each study area, the bar charts below display the percent of the total study area that changed each year by product (figure 6). For CLASlite and MLTA, deforestation and degradation are stacked in order to show the relative proportion of areas detected as undergoing deforestation compared to forest degradation. Additionally, the CLASlite products for Madang Province are only available biennially (figure 6a), making the rates of change somewhat misleading. Since the Hansen forest loss product does not have a separate forest degradation product, only a single bar is used to represent it. When looking at the graphs for each of the study areas, it is apparent that there are no clear long-term trends in the rate of deforestation and forest degradation. It also becomes apparent that each product detects different rates of change at different periods of time. This enhances the difficulty of gaining a meaningful understanding of the patterns of forest loss.

Some general patterns do, however, emerge between the different products. As discussed in the qualitative results section, the MLTA deforestation product generally provides a liberal estimate of deforestation, while the Hansen loss product is more conservative. We also see that the CLASlite product can be highly variable across the different study areas and in time. Most notable are the high rates of forest loss in the Mae Sa-Kog Ma Man and Biosphere Reserve study area indicated by the CLASlite product compared to the MLTA and Hansen products (figure 6d). CLASlite also has a much higher rate of detected deforestation and degradation in Madang Province.


A
Madang Province
0.80%
0.70%
0.60%
0.50%
0.40%
0.30%
0.20%
0.10%
0.00%
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
Hansen Forest Loss
MLTA Degradation
MLTA Deforestation
CLASlite Degradation
CLASlite Deforestation
B
Houaphan Province
3.50%
3.00%
2.50%
2.00%
1.50%
1.00%
0.50%
0.00%
2001
2002
2003
2004
2005
2006
2007
2008
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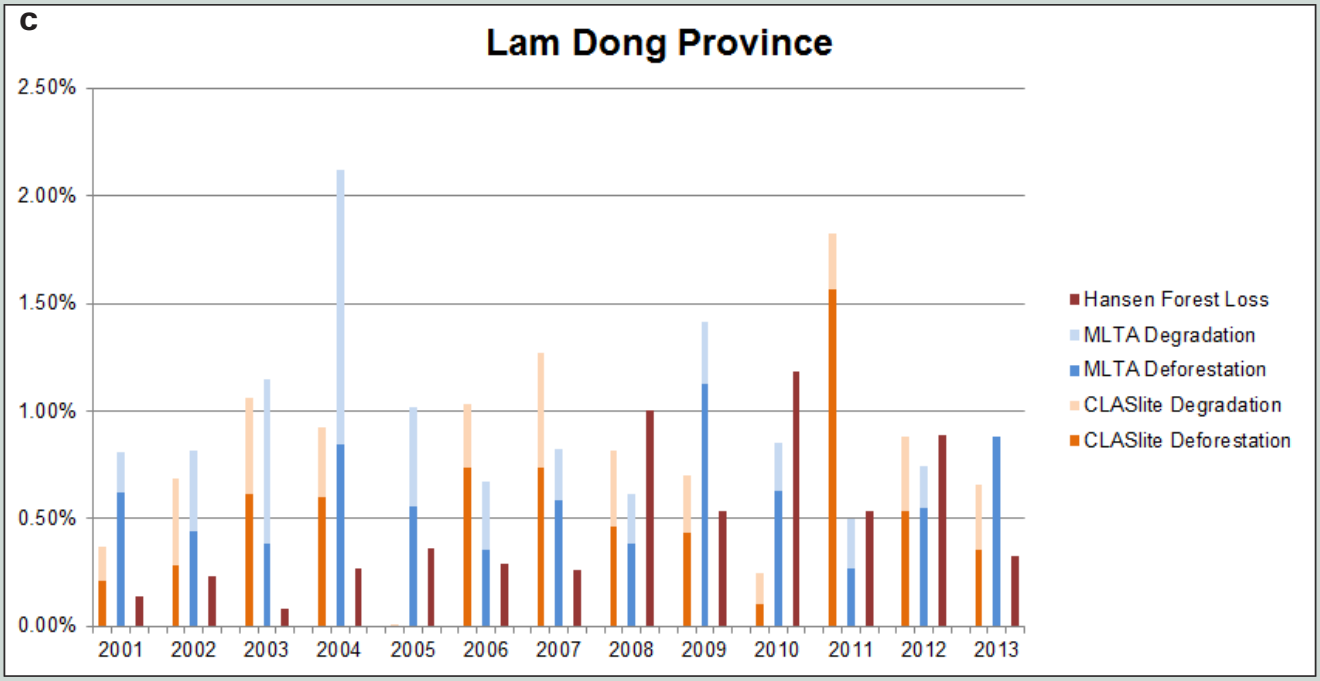
2011
2012
2013
Hansen Forest Loss
MLTA Degradation
MLTA Deforestation
CLASlite Degradation
CLASlite Deforestation



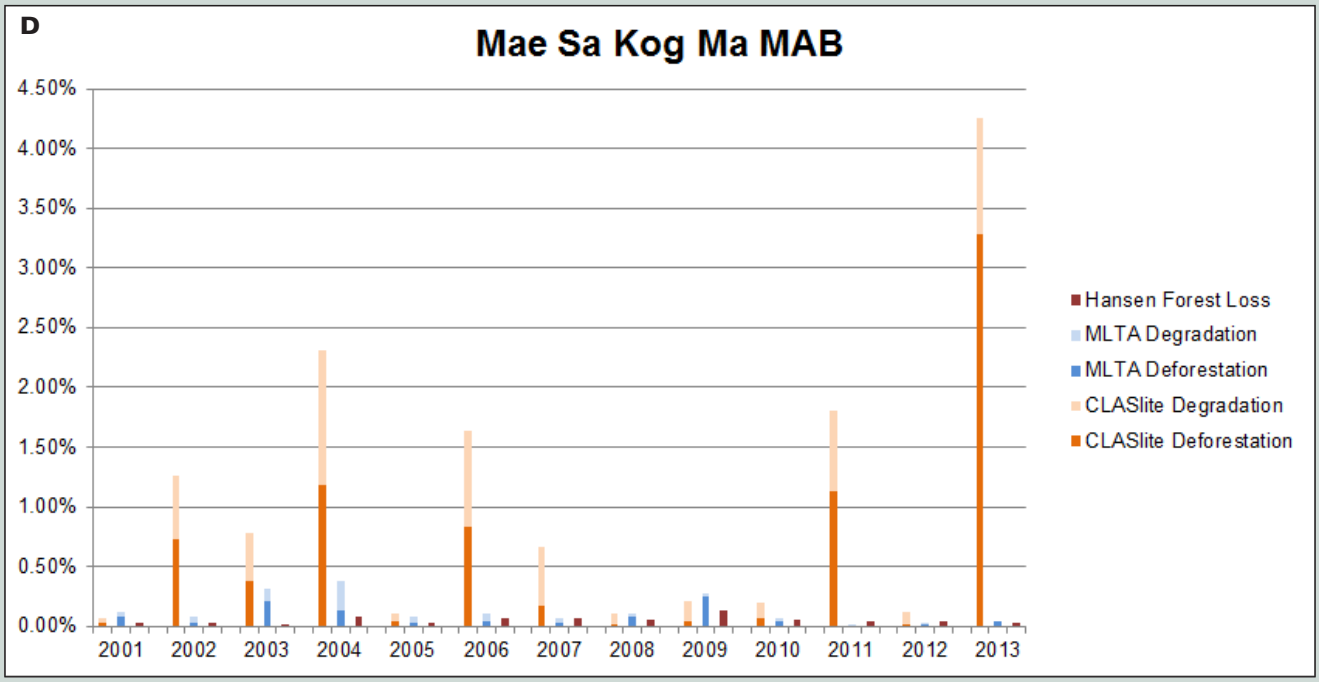


Figure 6—Deforestation and forest degradation rates across each study area for each product. No strong patterns of change rates emerged across time. It is clear that the CLASlite deforestation and degradation products tend to be variable across time and study area, while the Hansen product is generally conservative. The MLTA product tends to detect more deforestation than either product (except for in Mae Sa-Kog Ma Man and Biosphere Reserve), but is generally conservative with its estimate of degradation.

Combined Study area Quantitative Product Validation

The goal of the independent validation was to gain a quantitative understanding of the efficacy of the various forest loss algorithms. Primary challenges to this included:

- Lack of consistent analysis of forest change within image time series with abundant cloud cover
- Limited visual differences between forested areas and densely vegetated understory
- Timing of available observations relative to forest loss
- Difficulty of differentiating between forest recovery/regrowth and degradation

Despite these challenges, a total of 2,000 sample pixels were analyzed for the entire time series and categorized as undergoing deforestation, degradation, or no loss. While accuracy assessments ideally use an independent source of data to depict truth, the samples analyzed in TimeSync are believed to represent a useful depiction of what may be more likely to be truth, but not truth per se. With this in mind, all TimeSync-interpreted samples were used to try to gain a better understanding of the efficacy of each algorithm at detecting what analysts identified as deforestation and forest degradation.

We felt the most useful piece of information was the chance that an area detected as being deforested or degraded was actually deforested or degraded and, similarly, that an area that was, in fact, deforested or degraded was detected as such. These types of accuracy are often-times called user's and producer's accuracies. User's accuracy represents the proportion of samples identified as a given class by the algorithm that were also identified as the same class by the analyst. For example, a user's accuracy of 80 percent for forest loss would indicate that 80 percent of the samples identified by the algorithm as undergoing deforestation were also identified as such by the analyst. Producer's accuracy represents the proportion of samples identified as a given class by the analyst that were also identified as that class by the algorithm. For example, a producer's accuracy of 80 percent for forest loss would indicate that 80 percent of the samples identified by the analyst as undergoing deforestation, were likewise identified by the algorithm. This is of particular interest since it is suspected that the Hansen forest loss product does not detect degradation well. If this were the case, it would be expected that the producer's accuracy of the Hansen Forest Loss product for detecting degradation would be very low.

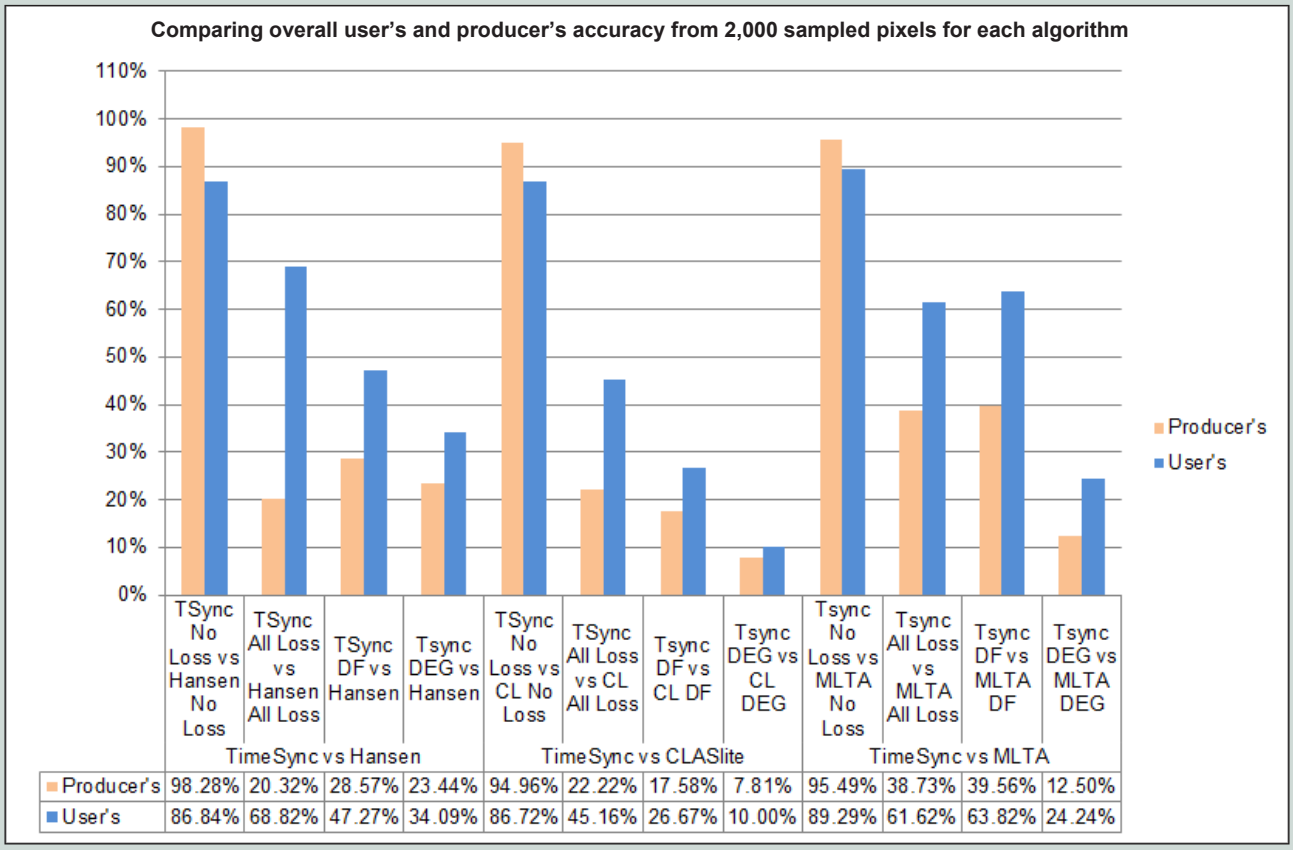
Figure 7 illustrates the user's and producer's accuracies between the different products and various combinations of classes. The broader four sections of bars are divided among algorithm output. Within each section, broader categories of interest are grouped. The first category is areas identified as undergoing no loss. The second is a combination of all loss where deforestation and forest degradation are combined. The other two groups compare deforestation and degradation respectively with TimeSync.

The first important highlight is that since the majority of the landscapes did not experience deforestation or forest degradation, both the user's and producer's accuracies are high for no loss categories. The second highlight is that the TimeSync-interpreted pixels indicate Hansen has a 23 percent producer's accuracy for the forest degradation class (23 percent of plots identified as degradation in Timesync were identified as forest loss by the Hansen product). This is higher than the producer's accuracy between TimeSync degradation and CLASlite degradation (18 percent) and MLTA degradation product (13 percent). This finding may come as a surprise to many users of the Hansen products. It is important to keep in mind that this is a depiction of forest degradation as we defined it for this project and is dependent on our ability to accurately depict forest degradation using TimeSync. Considering that the actual degradation products appear noisy and rather inconsistent between the two algorithms, finding such low accuracies is not surprising. The user's accuracy is higher in the MLTA deforestation category though, indicating that where the MLTA algorithm did identify deforestation, the plots were in relatively high agreement (64 percent).

Another pattern that is consistent across all products is that the accuracy for detecting degradation is much lower than for deforestation. This is expected since subtle low magnitude changes are more difficult to detect.

Discussion and Recommendations

As countries prepare systems to meet the increasing needs for improved forest cover monitoring, the role remote sensing can play often comes into question. Many available algorithms have been optimized to work in more ideal situations common in the mid-latitudes or even the Amazon. These methods do not provide a viable option for remote sensing-based monitoring systems in Southeast Asia. Recent work by Hansen et al. (2013) largely addresses the need for consistent, annually updated deforestation products, but fails to provide the flexibility that may be necessary to meet a specific country's monitoring needs for deforestation as well as forest degradation.



	TSync No Loss vs Hansen No Loss	TSync All Loss vs Hansen All Loss	TSync DF vs Hansen	Tsync DEG vs Hansen	TSync No Loss vs CL No Loss	TSync All Loss vs CL All Loss	Tsync DF vs CL DF	Tsync DEG vs CL DEG	Tsync No Loss vs MLTA No Loss	Tsync All Loss vs MLTA All Loss	Tsync DF vs MLTA DF	Tsync DEG vs MLTA DEG
	TimeSync vs Hansen				TimeSync vs CLASlite				TimeSync vs MLTA			
Producer's	98.28%	20.32%	28.57%	23.44%	94.96%	22.22%	17.58%	7.81%	95.49%	38.73%	39.56%	12.50%
User's	86.84%	68.82%	47.27%	34.09%	86.72%	45.16%	26.67%	10.00%	89.29%	61.62%	63.82%	24.24%

Figure 7—Graph depicting the user's and producer's accuracies across the different products for the 2,000 sampled pixels. Generally, detecting forest degradation proved more difficult than deforestation. The Hansen forest loss product had a higher producer's accuracy (detection rate) for forest degradation than CLASlite. MLTA had the highest producer's accuracy for all loss categories, indicating that perhaps it could serve as a viable option for future work.

With few to no cloud/cloud-shadow-free Landsat observations in Southeast Asia, it proved challenging to create cloud-free composites in all four study areas. Additionally, they contained some seasonal variation across individual composites. Many of these limitations are inherent with using Landsat as a sole data source. Despite these limitations, cloud free composites were successfully created using automated methods and then used in CLASlite.

This study addresses some of the regional challenges related to deforestation and forest degradation monitoring in Southeast Asia. The primary challenge for all forest cover loss monitoring methods proved to be the availability of high quality Landsat observations for the analysis period. This difficulty impacts methods that are automated, such as Hansen's forest loss, CLASlite, and MLTA, as well as manual approaches such as TimeSync. Despite all methods relying largely on the same dataset, null data artifacts do indicate that Hansen's Forest Loss and MLTA methods are generally more effective at handling irregularities in quality and frequency of available data that is inherent with using Landsat data in the tropics.

TimeSync proved to be a necessary tool to consistently assess forest loss and gain across time. Alternative tools such as Collect Earth (http://openforis.org/) provide some of the same capabilities in a Google Earth-centric environment, but lack the consistent visualization of the available Landsat archive. While all validation data collected in TimeSync were assumed to represent "truth," it is prone to interpretation error as well. Despite this potential shortcoming, the validation using TimeSync-based independent "truth" data did provide some useful insight into what methods may prove useful for future monitoring requirements in the region.

Unlike deforestation, detection of forest degradation continues to prove difficult using optical remote sensing. This study does indicate that all three forest change detection methods can detect forest degradation, but generally with higher error rates than for deforestation. Additionally, consistently detecting degradation is confounded by a lack of a consistent definition. The MLTA algorithm demonstrated the merits of having the ability to tailor the output to meet a specific definition but proved challenging to properly calibrate without enhanced on-the-ground knowledge of likely degraded areas. CLASlite proved effective at detecting

some degradation, but since the final change decision rule set was largely based on work in South America, the rules could not be adapted to degradation patterns in the USAID LEAF study areas. Based on the accuracy assessment comparison composed of 2,000 randomly selected points, the Hansen forest loss product proved to be more effective than expected at detecting forest degradation; however, presently it is not separated from deforestation or what Hansen refers to as "forest cover loss". While its producer's accuracy was relatively high compared to the other algorithms, it remained rather low in absolute terms. Perhaps with more calibration and field data a customized algorithm such as MLTA could be calibrated to more effectively detect forest degradation.

Next Steps

With the continuation of the Landsat program and the introduction of the Sentinel 2 mission (https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi/applications/land-monitoring), moderate resolution optical remote sensing-based monitoring systems should be able to provide increasing capabilities in the future. Currently, historical forest change analysis has many difficulties largely centered on the inconsistencies with Landsat 5 TM data acquisition and warehousing, and on Landsat 7 ETM+ scanline data gaps. Landsat 8 OLI now has difficulties with its thermal band, thus jeopardizing the ability to create robust cloud masks. The vulnerabilities of the Landsat program generally providing one sensor at a time will likely be mitigated with the Sentinel-2 mission.

Future methods will need to be able to harmonize the differences between the two missions' data to create seamless automated monitoring systems. Increasingly reliable data streams combined with distributed cloud-based computing environments, such as Google Earth Engine, will enable methods such as MLTA to be quickly tailored and applied to a monitoring need.

The final key component to automated repeatable forest degradation monitoring will be a standard definition that can be related to optical remote sensing data. Until a common definition is agreed upon, any method will need to remain highly tunable in order for a given definition to ensure potential efficacy. Additional enhancements with better data streams will also likely increase the ability to separate the subtle signal presented by forest degradation from the incessant noise.

References

Asner, G.P.; Knapp, D.E.; Balaji, A.; Paez-Acosta, G. 2009. Automated mapping of tropical deforestation and forest degradation: CLASlite. Journal of Applied Remote Sensing. 3(1): 033543–033543.

Cohen, W.B.; Zhiqiang, Y.; Kennedy, R.E. 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync—Tools for calibration and validation. Remote Sensing of Environment. 114(12): 2911–2924.

Gorelick, N. 2013. Google Earth Engine. In EGU General Assembly Conference Abstracts. [Place of publication unknown]: (15):11997.

Hammer, D.; Kraft, R.; Wheeler, D. 2009. FORMA: forest monitoring for action—rapid identification of pan-tropical deforestation using moderate-resolution remotely sensed data. Center for Global Development Working Paper. 192 p.

Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland,T.R.; Kommareddy, A.; Egorov, A.; Chini, L.; Justice,C.O.; Townshend, J.R.G. 2013. High-resolution global maps of 21st-century forest cover change. Science. 342(6160): 850–853.

Vogelmann, J.E.; Xian, G.; Homer, C.; Tolk, B. 2012. Monitoring gradual ecosystem change using Landsat time series analyses: Case studies in selected forest and rangeland ecosystems. Remote Sensing of Environment. 122: 92–105.

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