Environmental Research Communications

LETTER

Early warning tropical forest loss alerts in Peru using Landsat

Christian Vargas, Joselyn Montalban and Andrés Alejandro Leon

National Forest Conservation Program for Climate Change Mitigation, Ministry of the Environment, Lima, Peru

E-mail: geovargas@gmail.com

Keywords: early warning alerts, forest cover loss, Landsat, Humid tropical forest, Peru

Abstract

Since March 16, 2017, the National Forest Conservation Program for Climate Change Mitigation (PNCBMCC) of Peru’s Ministry of the Environment (MINAM) has been implementing a methodology to detect early warning alerts of humid tropical forest cover loss in Peru using data from the Landsat 7 and 8 satellites. The method uses Direct Spectral Unmixing (DSU) to detect forest loss as small as 25% of a pixel. Between March 16 and December 25 of 2017, 500 Landsat images have been used to detect 137,143 hectares of humid tropical forest cover loss, including deforestation for agricultural expansion and illegal or informal extractive activities, such as the opening of roads for selective logging. Natural forest loss was also detected, produced by windstorms and landslides in mountainous areas, among others. The results were verified with high-resolution satellite images and the accuracy was evaluated using a stratified random sample, showing a high level of both user’s and producer’s accuracy. The early warning alerts are distributed and available through the Geobosques platform (http://geobosques.minam.gob.pe).

1. Introduction

Global warming has been of increasing concern in recent years, produced by higher greenhouse gas (GHG) emissions from different economic sectors at a global scale. In Peru, the land use, land use change, and forestry sectors (LULUCF) contribute the most emissions, representing 51% of total emissions (MINAM 2016), and primarily due to the deforestation of humid Amazonian forests. This dynamic has incentivized public and private institutions to develop, propose and execute research on remote sensing for forest monitoring, given that it can cover a wide area in a reasonable time and provide verifiable information for decision making on monitoring, control, and sanctioning of deforestation.

There are currently many methods for early detection and monitoring of forest loss or change using low- and medium-resolution images. Methods like Forest Monitoring for Action (FORMA) (Hammer et al 2014) and Terra-i (Reymondin et al 2012) use data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. The Break for Additive Season and Trend method (BFAST) (Verbesselt et al 2012) combines different types of time series to detect forest disturbance. Brazil, through the National Institute for Space Research (INPE) has a project to detect deforestation in near-real-time (The Real-Time Deforestation Detection System, DETER), with data published monthly on deforestation and degradation using MODIS (Shimabukuro et al 2012). The Deforestation Alert System (SAD) uses MODIS images and the Normalized Difference Fraction Index (NDFI) (Souza et al 2005) to detect deforestation in the state of Mato Grosso in Brazil (Souza et al 2009). Two new algorithms that use MODIS data for the rapid detection of forest disturbances (Tang et al 2019) were proposed recently. Although these algorithms have better results than Terra-i, their nationwide operation has not yet been tested. The main limitation of the use of low spatial resolution data such as MODIS (250 m) is that they are not able to detect small-scale deforestation events. In 2016, 72% (116,910 ha) of deforestation in tropical humid forests of Peru occurred in patches of less than 5 ha (http://geobosques.minam.gob.pe/geobosque/view/perdida.php). This indicates that, MODIS would potentially detect less than 28% of the deforestation that is actually happening. In 2016, the Global Land Analysis and Discovery (GLAD) lab in the Department of...
Geographical Sciences at the University of Maryland presented a prototype for forest disturbance alerts in humid tropical forests for Peru, the Republic of Congo, and Kalimantan, Indonesian using data from the ETM + and OLI sensors (Hansen et al 2016). These data have a spatial resolution of 30 m, which allows detecting small-scale deforestation. Currently those alerts are available for more than 20 countries. New methodologies have reported the combined use of optical data and Synthetic Aperture Radar (SAR) in the detection of deforestation (Reiche et al 2018, Perbet et al 2019). This minimizes the bias between the date the image was taken and the date on which deforestation occurred.

In 2012, with the support of the SilvaCarbon program, the Department of Geographical Sciences at the University of Maryland began providing technical assistance to PNCMBCC for the mapping of humid tropical forest loss for the period 2000 to 2011 (Potapov et al 2014, MINAM 2015a), with support continuing in subsequent years. In December 2015, the Norwegian Agency for Development Cooperation (NORAD) approved a project for the implementation of the Joint Declaration of Intention for REDD + between Peru, Norway, and Germany, signed by the World Wildlife Fund and the PNCBMCC (DCI—WWF). Within the framework of this agreement, a preliminary method was developed for the early detection and quantification of humid Amazonian forest loss in Peru using data from Landsat 8 (Vargas et al 2017), in order to facilitate the creation of a nationally-owned forest monitoring system in the future. In parallel, in January 2016 the PNCBMCC and the World Resources Institute (WRI) signed a data sharing agreement, through which PNCBMCC received information for the GLAD alerts. In the second week of March 2017, the GLAD lab stopped producing the alerts temporarily, and the PNCBMCC had no information to report to its users. Given this lack of information, the PNCBMCC implemented its own methodology, which is an update of the preliminary method proposed by Vargas et al (2017). With this, the PNCBMCC has achieved independence in the generation of data and managed to improve the detail of detection of forest cover loss, contributing to the sustainability of monitoring of humid tropical forest in Peru.

This document describes the methodological process and results of the method used for the detection of early warning humid tropical forest alerts in Peru implemented by PNCBMCC.

2. Study area

The study area is Peru’s humid tropical forests (figure 1), which cover an area of 78,308,801 hectares and represent 60.9% of the country (MINAM 2012). Peru is considered a country with a large extension of forests and a moderate annual deforestation rate, in which the forest conversion predominates mainly due to agricultural activity, artisanal mining, and industrial agriculture (Potapov et al 2014) (MINAM 2016). The annual average deforestation for the period 2000–2011 was 106,890 hectares (MINAM 2015b). According to the forest loss data published by PNCBMCC (http://geobosques.minam.gob.pe/geobosque/view/perdida.php), the annual average deforestation for 2012–2016 was 159,688 hectares compared to the 2006–2016 average 142,224 hectares, showing a considerable increase in deforestation in recent years.

The early warning alerts were detected on the primary forest available for the year 2016, this layer is updated every year by the PNCBMCC.
3. Data

The method used the blue (0.45–0.52 μm), green (0.52–0.60 μm), red (0.63–0.69 μm), near infrared (0.77–0.90 μm), shortwave infrared 1 (1.55–1.75 μm), and shortwave infrared 2 (2.09–2.35 μm) bands from the Landsat Enhanced Thematic Mapper Plus (ETM+) sensor onboard Landsat 7 and the ultra-blue (0.435–0.451 μm), blue (0.452–0.512 μm), green (0.553–0.590 μm), red (0.636–0.673 μm), near infrared (0.851–0.879 μm), shortwave infrared 1 (1.556–1.651 μm) and shortwave infrared 2 (2.107–2.294 μm) bands from the Operational Land Imager (OLI) sensor onboard Landsat 8. All images were downloaded from https://earthexplorer.usgs.gov/ and correspond to collection 1, they have Precision and Terrain Correction (L1TP), and a spatial resolution of 30 m. Landsat 7 and Landsat 8 satellites have a temporary resolution of 16 days, which indicates that we could potentially have images of the same place every 8 days.

For the period 2013–2016, two sets of the best images per year were downloaded and used to extract forest endmembers and forest loss, and for 2017 all available images between March 16 and December 25 were downloaded and used to detect the loss of forest. All images were calibrated to Top of the Atmosphere (TOA) reflectance. For the classification of clouds, haze, and shadows, a set of binary rules implemented in a decision tree was used. These rules were generated based on the spectral response of clouds, haze and shadows of 30 Landsat ETM + and OLI images. The edges of the clouds are difficult to classify, due to the spectral mixture they have with other materials. To ensure their detection, a dilation filter was applied with a 5 × 5 window. To standardize the projection and maintain coherence with maps of primary forest and annual forest loss generated by MINAM. All work was done in UTM, zone 18 S, datum WGS84.

4. Method

4.1. Direct spectral unmixing (DSU)

To detect the early warning alerts, we developed a new method, called Direct Spectral Unmixing (DSU). DSU is based on Linear Spectral Mixing Model (LSMM), which provides quantitative information of the materials that make up the pixel. LSMM assumes that the spectral response of a pixel is the linear combination of the materials that are inside the pixel (Endmembers) (Smith et al 1990, Bateson et al 1996, Tompkins et al 1997, Roberts et al 1998, Shimabukuro et al 2017). The selection of endmembers is a fundamental step for the application of LSMM there are many techniques and proposals for endmember selection (Smith et al 1990, Roberts et al 1993, Dennison and Roberts 2003, Lu et al 2003a, Asner et al 2009). LSMM is used frequently in the detection of burned areas, deforestation, and forest degradation (Adams et al 1995, Arai et al 2011, Cochrane and Souza 1998, Lu et al 2003b, Souza et al 2005, Asner et al 2009, Souza et al 2009, Shimabukuro et al 2014). These studies use 3 or 4 endmembers, usually photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), soil, and/or clouds.

DSU only uses endmembers of forest and forest loss, and assumes that when a pixel loses forest cover from natural or anthropogenic causes, the result may be a pixel with bare soil, a mixed pixel with soil and dry vegetation, or residuals of deforestation like tree trunks which may also be mixed in with standing forest. The endmembers used in this study were obtained from Landsat images. The advantage of extracting endmembers directly from the images is the ease with which they can be obtained, and the similarity in scale to the data (Roberts et al 1998). The forest endmember is the average of the spectral response from primary forest, obtained by taking the minimum and maximum reflectance values from the composite of images for the period 2013–2016 through a random sample of pixels that coincides with the primary forest layer of the year 2016. The endmember of forest loss is the average of the spectral signature of forest loss, obtained using a random sample of pixels with the highest probability of being deforested during the period 2013–2016. These endmembers were used to create a LSMM, which models the spectral behavior of distinct percentages of forest cover loss within a pixel (see figure 2).

A common problem of spectral unmixing is to be able to estimate the percentage of each class within a pixel (Schowengerdt 2007). DSU solves this problem in a practical way by applying the ratio between the SWIR1 and NIR bands for each percent of forest cover loss in the LSMM, obtaining thresholds that relate directly with the percent of forest cover loss within a pixel. Figure 3 shows the RapidEye image taken on 10/05/2017 with two deforested areas. In this image the percentage of loss of forest cover was obtained by applying DSU in a Landsat 8 image taken on 10/10/2017. It can be seen that, at the edges of the deforested area, DSU allowed the calculation of the percentage of loss of forest cover within the Landsat pixel.

4.2. Detection of early warning alerts

Within the forest area defined by the 2016 primary forest layer, early warning alerts were detected weekly starting at March 16, 2017. In order to achieve this, we integrated the TOA reflectance of all Landsat ETM + and OLI
images into mosaics and applied a binary decision tree that includes cloud, haze and shadow classification with the detection thresholds of forest cover loss. With the OLI images, the threshold was set to detect up to 25% forest cover loss over low slopes and up to 35% forest cover loss in areas with mountainous relief. This differentiation avoids the possible detection of false positives in areas of forests with mountain shadows. The 35% threshold was also used with ETM + images. This threshold was used to avoid false positive detection due to the possible presence of low-density clouds that could not be classified in the data; these clouds are detected using the ultra-blue band, which is absent in the ETM + sensor. Finally, in the forest loss layer we deleted the pixels that intercept with clouds or haze with dilation filter with a 5 × 5 window.

The date on which the loss of forest cover is detected corresponds to the date of the ETM + or OLI image used, and ideally, the data show no presence of clouds. The actual date on which the loss of forest cover occurred should not be more than 8 days prior to the date of the ETM + or OLI image used for its detection.

The early warning alerts detected each week are used as an auxiliary layer within the binary decision tree in order to avoid repeated detections in following weeks. The early warning alerts are published and distributed through the Geobosques platform of PNCBMCC. Figure 4 shows the flow diagram for the detection and distribution of early warning alerts.

4.3. Comparison with GLAD data
As mentioned in the introduction, this methodology is developed to support the sustainability of monitoring and improving the detail of detection of forest cover loss. In order to know if we were able to improve the detection of the loss of forest cover, we compared our results with the early warning alerts of the Global Land Analysis and Discovery (GLAD) lab of the UMD. These alerts reach up to 50% detection of forest cover loss within a pixel of Landsat (Hansen et al 2016). The data of the year 2017 were downloaded from the GLAD website (http://glad-forest-alert.appspot.com/) On May 15, 2018, the data were reprojected to UTM, zone 18 S, datum WGS84 and only the early warning alerts that coincided with the primary forest layer for 2016 were used.
4.4. Verification and accuracy assessment

Satellite images available on the Planet Platform were used for the verification and accuracy assessment of the early warning alerts. The costs associated with the use of this platform were covered by the DCI - WWF project. This platform is characterized by having satellite data with high spatial and temporal resolution (Doves and RapidEye images with a spatial resolution of 3 m and 5 m respectively). Sentinel-2 10 m spatial resolution bands were also used. The use of these images ensures that the reference data used to evaluate our results is better than that applied to generate the information (Olofsson et al 2014). In addition, the use of high spatial resolution images minimizes uncertainty in the interpretation of sample units.

The early warning alerts were visually verified using available images from the Planet platform ((Dove and RapidEye). The largest deforestation events are described in official reports, where images from Planet and Sentinel-2 are used to show the before and after of a deforestation event. These reports can be found in the ATD category-monitoring files of the downloads section of the Geobosques platform (http://geobosques.minam.gob.pe/geobosque/view/descargas.php).

To understand the accuracy of forest loss detection, we used a stratified random sample. We decided to use this sampling method due to the need to know the accuracy of the early warning alerts detected in low slopes and mountainous areas, added to the advantage of having access to images of the Planet platform for the entire humid tropical forest. We created the following four strata: forest cover loss/non-forest cover loss in mountainous areas and forest cover loss/non-forest cover loss in low slopes). The stratum of forest cover loss corresponds to the early warning alerts detected until 10/18/2017, which amount to 117 240 ha of the total detected. This is because our access to the Planet Platform was available until 12/31/2017 and because the months of October, November and December correspond to the humid season, where satellite images have a high presence of clouds. By doing this, we reduced the probability of having sample units that cannot be interpreted due to the presence of clouds. The non-forest cover loss stratum corresponds to the 5-pixel buffer around the detected early warnings that coincide with the primary forest layer of 2016. This prevents us from having random sample units in non-forest areas or deforested areas before 2017, so that sampling in this stratum is restricted to areas with the highest probability of having deforestation events, which commonly occur in areas adjacent to deforested lands. Figure 5 shows an example of the forest cover loss and non-forest cover loss strata, and it also depicts how non-forest areas were excluded from the non-forest cover loss stratum.
The forest cover loss and non-forest cover loss strata were subdivided using a layer of lowland forest and mountain forest that was created using the vegetation map of MINAM (MINAM 2012). In total, a single sample of 1384 sample units was used at the pixel level. The distribution of sample units was proportional to the area of pixels of the strata within the low sloped forest and forest in mountainous zones, resulting in 988 and 396 sample units, respectively. Then, these sample units were distributed equally among each stratum. Table 1 shows the number of pixels, their equivalent area and the sample units used for each stratum.

The interpretation of sample units was performed by an expert not involved in the alert generation process. Each sample unit (pixel) was interpreted using Planet (Dove and RapidEye) or Sentinel-2 images. Sample units with presence of forest cover loss were labeled with the number 1 and sample units with presence of forest were labeled with the number 0. A confusion matrix was created based on these interpreted sample units, with accuracy figures for each stratum and 95% confidence intervals.

5. Results and discussion

5.1. Early warning alerts

Between March 16 and December 25 of 2017, a total of 137,143 hectares of humid tropical forest cover loss were detected. Of detected alerts, 78.8% occurred in low slope areas, while 21.2% occurred in areas with mountainous relief.

In order to know the areas with the highest density of early warning alerts, we developed a point density map —while previously, early warning alerts used to be converted to vector format— and we used a radius of 5000 m, which shows areas with the highest density of early warning alerts in red and the areas with lower density in green. The highest density of early warning alerts occurred in the regions of Madre de Dios, Ucayali, and Huánuco (see figure 6).

In Madre de Dios, the biggest patch of deforestation detected was more than 480 ha. Using visual interpretation, it was estimated that 7,713 ha of forest loss was due to illegal mining, representing 5.6% of all detected forest loss. In the case of the Ucayali and Huánuco regions, the highest density of alerts is found in the

| Stratum                              | Total pixels | Area (ha)  | Sample units |
|--------------------------------------|--------------|------------|--------------|
| Forest cover loss in low-slope areas | 1 044 888    | 94039.92   | 494          |
| Non-forest cover loss in low-slope areas | 8 740 365    | 786 632.9  | 494          |
| Forest cover loss in mountainous areas | 257 779      | 23200.11   | 198          |
| Non-forest cover loss in mountainous areas | 3 789 113    | 341020.2   | 198          |
area near the Jorge Basadre Highway and the road connecting Codo del Pozuzu and Puerto Inca. In these regions, 1360 patches of more than 5 ha were detected, attributable to large- and medium-scale agriculture and livestock activity. There were also 109 patches of deforestation larger than 20 ha, totaling 4085 ha. Based on the historical dynamics of deforestation, these areas are attributed to extensive cattle ranching and agro-industrial cultivation (MINAM 2016).

Based on a weekly basis analysis, 65% of patches were smaller than 1 ha. However, if we look at patch size considering the entire study period, that figure decreases to 46%, with more patches topping 1 and even 5 ha (see figure 7). This shows the evolution of patches over time, as primary forest loss starts small and becomes larger over time.

From the above, it can be determined that there is a 19% decrease in the patches of forest cover loss smaller than 1 ha, which have been redistributed to patches larger than 1 ha, and that forest cover loss patches greater than 5 ha increased by more than 50%. For example, of the 480 ha of forest loss detected in Madre de Dios, 36 ha were detected in March, the highest deforestation happened in August and September with more than 280 ha, and deforestation continued until December (see figure 6). This indicates that the deforestation driver remains active during the humid and dry seasons.

The threshold of detection of up to 25% of forest cover loss in a pixel permits the detection of some forest degradation events such as selective logging and opening of roads. In total, 1416 km of roads wider than 7.5 meters were detected by the alerts, most of which are located in the regions of Madre de Dios, Ucayali and Loreto. Figure 8 shows examples of road detection and some selective logging events.

The highest detection of early warning alerts occurred in the dry months. This is because deforestation associated with activities such as agriculture, livestock and selective logging takes place in this season since it is easier to access a land, burn it, clear it and sow it. This also coincides with the greater availability of images with lower percentage of clouds. However, deforestation caused by illegal mining can start in the humid season.
5.2. Comparison with GLAD data
Between March 16 and December 25, 2017, it was possible to detect 137,143 ha of forest cover loss, while for the same period, GLAD detected 99,958 ha. The multitemporal comparison of the number of hectares detected by both methodologies shows in most cases the early warnings of Geobosques detected more hectares of forest cover loss, starting in the month of August (see figure 9).

GLAD detected 983 km of roads. The early warning alerts of Geobosques detected 433 km of roads that were not detected by GLAD. This shows a significant advantage in detecting the opening of roads, which are commonly used for selective logging. Figure 10 shows the detection of roads made by the early warning alerts of Geobosques and GLAD. The detection of up to 25% of forest cover loss within a pixel allowed detecting more forest cover loss by the opening of roads.

Both methods have a low detection of forest loss in the humid season and a greater detection in the dry season, since in this season there is a greater probability of obtaining images with low percentage of clouds.

5.3. Accuracy assessment
Table 2 shows the confusion matrix, accuracy and confidence intervals obtained for the early warning alerts. The user’s and producer’s accuracies for the forest cover loss stratum in mountainous areas were 97.0% and 95.0%, respectively, while for the forest cover stratum in low-slope areas the accuracies were 94.9% and 91.6%, respectively. The user accuracy in both strata is high, which means that our commission error is low, while the
producer’s accuracy, which indicates the omission of forest loss pixels, has a lower value in the forest cover loss stratum in low-slope areas. This is likely due to the dilation filter that was applied to clouds, which partially or totally eliminated the forest loss found next to clouds. The overall accuracy obtained was 93.9%.

The early warning alerts are updated weekly and distributed through the Geobosques platform from PNCBMCC of MINAM (http://geobosques.minam.gob.pe). Geobosques has more than 2500 subscribers who receive information about alerts in their areas of interest via email (see appendix).

6. Conclusions

The method developed provides weekly information on the loss of humid tropical forest cover in Peru. The methodology uses a large amount of Landsat data and the method developed allows for high accuracy. This assures the reliability of the data to support authorities responsible for forests with accurate information on primary forest loss.

The direct spectral unmixing (DSU) method permits the selection of a threshold for the minimum percent of forest cover loss within a pixel. This provides consistency and comparability between the data and the use of the

Table 2. Confusion matrix and confidence intervals for the analyzed strata.

| Reference | NFCL-L | FCL-L | NFCL-M | FCL-M | Total | User’s accuracy |
|-----------|--------|-------|--------|-------|-------|----------------|
| Map       |        |       |        |       |       | User’s accuracy |
| NFCL-L    | 451    | 43    | 0      | 0     | 494   | 91.3% ±2.5     |
| FCL-L     | 25     | 469   | 0      | 0     | 494   | 94.9% ±1.9     |
| NFCL-M    | 0      | 0     | 188    | 10    | 198   | 94.9% ±3.1     |
| FCL-M     | 0      | 0     | 6      | 192   | 198   | 97.0% ±2.4     |
| Total     | 476    | 512   | 194    | 202   | 1384  |                |
| Producer’s accuracy | 94.7% ±0.7 | 91.6% ±0.6 | 96.9% ±4.4 | 95.0% ±6.9 | Overall accuracy | 91.3% ±2.5 |

Figure 10. Example of road detection with early warnings alerts of Geobosques (top) and GLAD (bottom) in the northern part of Madre de Dios.
detection threshold of up to 25% of forest cover loss in a pixel, which allowed us to detect roads that were not detected by GLAD’s early warning alerts.

The analysis of forest cover loss patch size shows that 19% of the forest loss that was initially detected as less than 1 ha had become a larger area of deforestation by the end of the year. This dynamic provides an opportunity for the responsible authorities to evaluate the legality of the deforestation and take corrective action to stop deforestation in areas that don’t have an authorization for land use change.

Most alerts were detected in months with the least cloud cover. To help overcome the limited availability of optical data when there is presence of clouds, the Japan International Cooperation Agency (JICA) has been working with the PNCBMCC and the National Forest and Wildlife Service (SERFOR) to apply Synthetic Aperture Radar (SAR) data in the early detection of forest cover loss. UAS systems can also be used for monitoring small areas and support in covering gaps of information related to the presence of clouds in the optical data.

The methodological process described here only uses spectral bands that are also available in Sentinel-2 data, with the thought that in the future these data can also be used in the next generation of early warning alerts.

Acknowledgments

The authors thank the Global Forest Watch team, the SilvaCarbon Program, and the anonymous reviewers that helped to improve this article.

Appendix

Geobosques platform

Geobosques is a web platform (http://geobosques.minam.gob.pe) that provides official and timely data and information on forest cover changes for planning and decision-making in forest management. This information is distributed in geospatial formats (raster and vector) and statistical data (excel files and reports).

Geobosques information is organized in five sub-modules of information: deforestation, early warning alerts, degradation, land use, land use change and reference level.

Information of early warning alerts can be accessed through the Geobosques viewer (http://geobosques.minam.gob.pe/geobosque/visor/), which provides updated information on the detection of early warning alerts in the humid tropical forest of Peru. Figure A1 shows the Geobosques viewer, displaying areas with the highest density of early warning alerts in red. It is also possible to compare the detected number of hectares of

Figure A1. Geobosques viewer with different layers that can be superimposed on the base map.
In order to promote the use of these deforestation monitoring tools in Peru, the PNCBMCC has been carrying out capacity building activities at the level of subnational governments (regional and local governments) and their allies in forest conservation (public and private institutions, indigenous organizations, among others), to improve forest management. Until July 2019, Geobosques had 1530 registered users who receive information on early warning alerts via email and are able to download these data in order to plan verification, prevention and/or control actions for activities that cause deforestation. Figure A2 shows the distribution of Geobosque users.

The free provision and availability of this information to the general public has earned 2 awards for the PNCBMCC, who manages the Geobosques Platform: the Special Award on Open Data in Public Management in September of 2018 and the Connect to Grow Award in November of 2018.

ORCID iDs

Christian Vargas  @ https://orcid.org/0000-0003-4793-4858
Joselyn Montalban  @ https://orcid.org/0000-0001-7741-105X
Andrés Alejandro Leon  @ https://orcid.org/0000-0003-1674-0284

References

Adams, J. B., Sabol, D. E., Kapos, V., Almeida Filho, R., Roberts, D. A., Smith, M. O., Gillespie, A., et al. (1995). Classification of multitemporal images based on fractions of endmembers: application to land-cover change in the Brazilian Amazon. Remote Sens. Environ. 52, 137–154.

Asner, G. P., Knapp, D. E., Balaji, A., and Paez-Acosta, G. (2009). Automated mapping of tropical deforestation and forest degradation: CLASLite. J. Appl. Remote Sens. 3, 033543.

Bateson, A. M., and Curtiss, B. (1996). A method for manual endmember selection and spectral unmixing. Remote Sens. Environ. 55, 229–243.

Cochrane, M. A. (1998). A linear mixture model classifier for burned forests in the Eastern Amazon. Int. J. Remote Sens. 19, 3433–3440.

Dennison, P. E., and Roberts, D. A. (2003). Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE. Remote Sens. Environ. 87, 123–135.

Hammer, D., Kraft, R., and Wheeler, D. (2014). Alerts of forest disturbances from MODIS imagery. Int. J. Appl. Earth Obs. Geoinf. 33, 1–9.

Hansen, M. C., Krylov, A., Tuia, D., Potapov, P., Turubanova, S., Tyukavina, A., Zutta, B., and van derMerwe, S. (2013). High spatial and temporal resolution monitoring of Amazon deforestation. Environ. Res. Lett. 8, 034008.

Lu, D., Batistella, M., and Moran Emilio, M. (2003). Detecting Amazonian deforestation using multitemporal thematic mapper imageries and spectral mixture analysis. ASPRS Annual Conference (Anchorage, Alaska, 2003).

MINAM 2016. Estrategia nacional sobre bosques y cambio climático. Lima, Perú: MINAM.

MINAM 2015b. Memoria descriptiva del mapa de bosque no bosque para el año 2000 y pérdida de los bosques húmedos amazónicos del Perú 2000–2011. Lima, Perú: MINAM.

MINAM 2012. Memoria Descriptiva del Mapa de Cobertura Vegetal Del Perú. Lima, Perú: MINAM.
MINAM 2015a Protocolo de clasificación de pérdida de cobertura en los bosques húmedos amazónicos entre los años 2000–2011. Lima, Perú: MINAM

Olofsson Pontus, Foody Giles M, Herold Martin, Stehman Stephen V, Woodcock Curtis E and Wulder Michael A 2014 Good practices for estimating area and assessing accuracy of land change Remote Sens. Environ. 148 42–57

Perbet Pauline, Fortin Michelle, Ville Anouk and Beland Martin 2019 Near real-time deforestation detection in Malaysia and Indonesia using change vector analysis with three sensors International Journal of Remote Sensing 40 7439–7458

Potapov P V, Defewolff I, Takero Y, Hansen M C, Stehman S V, Vargas C, Rojas E J, Castillo D, Mendoza E, Calderon A, Giudice R, Malaga N, Zutta B R et al 2014 National satellite-based humid tropical forest change assessment in Peru in support of REDD + implementation Environmental Research Letters 9 124012 National satellite-based humid tropical forest change assessment in Peru in support of REDD + implementation

Reiche Johannes, Hamunyela Eliakim, Verbesselt Jan, Hoekman Dirk and Herold Martin 2018 Improving near-real time deforestation monitoring in tropical dry forests by combining dense Sentinel-1 time series with Landsat and ALOS-2 PALSAR-2 Remote Sens. Environ. 204 147–161

Reymondin Louis, Jarvis Andrew, Perez-Uribre Andres, Touval Jerry, Argote Karolina, Coca Alejandro, Rebetez Julien, Guevara Edward, Mulligan Mark et al 2012 Terra-i: a methodology for near real-time monitoring of habitat change at continental scales using MODIS-NDVI and TRMM. CIAT-Terra-i

Roberts Dar A, Batista Getulio T, Pereira Jorge L G, Waller Erick K and Nelson Bruce W 1998 Change identiﬁcation using multispectral spectral mixture analytic application in Eastern Amazonia Remote sensing change Detection: Environmental Monitoring and Applications ed Ros Lunetta and Christopher Elvidge (Chelsea. Michigan 48118: Ann Arbor Press) 137–161

Roberts D A, Smith M O and Adams JB 1993 Green vegetation, nonphotosynthetic vegetation, and soils in AVIRIS data Remote Sensing of Environment 44 253–269

Schowengerdt R A 2006 Subpixel classiﬁcation Remote sensing: Models and Methods for Image Processing ed R A Schowengerdt Third (Orlando, FL, USA: ESEvier)

Shimabukuro Yosio E, Egidio Arai, Duarte Valdete, Anderson Liana O, Cruz de Aragao Luiz E O, Achard Frederic, Beuchle Rene, Simonetti Dario and Grecchi Rosana C 2017 Monitoring deforestation and forest degradation in the Amazon basin using multitemporal fraction images derived from Sentinel-2 sensor data XVIII Simpósio Brasileiro de Sensoriamento Remoto-SBSR 28 - 31 May1218–1225

Shimabukuro Yosio E, Dos Santos Joao R, Formaggio Antonio R, Duarte Valverde and Friedrich Theodor Bernardo Friedrich 2012 The Brazilian amazon monitoring program: PRODES and DETER projects Global Forest Monitoring from Earth Observation ed Frederic Achard and Matthew Hansen (Boca Raton, FL: CRC Press) 9 167-183 Achard Frederic, Matthew and Hansen C

Shimabukuro Yosio E, Beuchle Rene, Grecchi Rosana C and Frédéric Achard 2014 Assessment of forest degradation in Brazilian Amazon due to selective logging and fires using time series of fraction images derived from Landsat ETM + images Remote Sensing Letters 5 773–782

Smith Milton O, Ustin Susan L, Adams John B and Gillespie Alan R 1990 Vegetation in deserts: I. A regional measure of abundance from multitemporal images Remote Sensing of Environment 31 1–26

Souza Jr Carlos M, Robert Dar A and Cochrane March A 2005 Combining spectral and spatial information to map canopy damage from selective logging and forest fires Remote Sensing of Environment 98 329–343

Souza Jr Carlos M, Hayashi Sanie and Verissimo Adalberto 2009 Near real-time Deforestation Detection for Enforcement of forest Reserves in Mato Grosso Land Governance in Support of the Millennium Development Goals: Responding to new Challenges FIG - World Bank Conference (Washington DC, 9–10 March 2009)

Tang Xiaojing, Bullock Erick L, Olofsson Pontus, Estel Stephan and Woodcock Curtis E 2019 Near real-time monitoring of tropical forest disturbance: New algorithms and assessment framework Remote Sensing of Environment 224 202–218

Tomplins Stefanie, Mustard John F, Pieters Carle M and Forsyth Donald W 1997 Optimization of endmembers for spectral mixture analysis Remote Sensing of Environment 59 472–489

Vargas Christian, Taquia Andres A, Hinostroza Peter G, Gutierrez Freddy R and Briosi Urpi T 2017 Metodología preliminar para la detección y cuantificación temprana de la pérdida de bosques húmedos tropicales de Perú usando Landsat 8 XVII-Simposio Brasileiro de Sensoriamento Remoto - SBSR 28 - 31 May 6468-6474

Verbesselt Jan, Zeileis Achim and Herold Martin 2012 Near real-time disturbance detection using satellite image time series Remote Sensing of Environment 123 96–108