A spatial pattern analysis of forest loss in the Madre de Dios region, Peru

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Abstract
Over the past decades, the Peruvian Amazon has experienced a rapid change in forest cover due to the expansion of agriculture and extractive activities. This study uses spectral mixture analysis (SMA) in a cloud-computing platform to map forest loss within and outside indigenous territories, protected areas, mining concessions, and reforestation concessions within the Madre de Dios Region in Peru. The study area is focused on key areas of forest loss in the western part of the Tambopata National Reserve and surrounding the Malinowski River. Landsat 8 Operational Land Imager and Landsat 7 Enhanced Thematic Mapper Plus surface reflectance data spanning 2013–2018 were analyzed using cloud-based SMA to identify patterns of forest loss for each year. High-resolution Planet Dove (3m) and RapidEye (5m) imagery were used to validate the forest loss map and to identify the potential drivers of loss. Results show large areas of forest loss, especially within buffer zones of protected areas. Forest loss also appears in the Kotsimba Native Community within a 1 km buffer of the Malinowski River. In addition to gold mining, agriculture and pasture fields also appear to be major drivers of forest loss for our study period. This study also suggests that gold mining activity is potentially not restricted to the legal mining concession areas, with 49% of forest loss occurring outside the mining concessions. Overall accuracy obtained for the forest loss analysis was 96%. These results illustrate the applicability of a cloud-based platform not only for land use land cover change detection but also for accessing and processing large datasets; the importance of monitoring not only forest loss progression in the Madre de Dios, which has been increasing over the years, especially within buffer zones, but also its drivers; and reiterates the use of SMA as a reliable change detection classification approach.

1. Introduction
During the 1980s and 1990s, the loss of natural forests in the Madre de Dios region, a biodiversity hotspot in the southwestern Amazon [1, 2], was primarily caused by government subsidized agricultural expansion [3, 4]. However, in the 2000s, gold mining became an important driver of regional land use and land cover dynamics [5]. The Peruvian Government’s reports on annual forest loss show that rates in the Madre de Dios have been increasing since 2001, reaching its peak rate in 2017, when this department had the second highest rate of forest loss in Peru [6]. One of the main reasons for this was the growth of the Interocenatic Highway which facilitated access to previously isolated forests and gold exploration sites [5, 7, 8].

Recent studies [9–11] and independent groups [12] have monitored the expansion of gold mining activities in this region, showing that artisanal and small-scale gold mining (ASGM) activities are responsible for a large fraction of forest loss. ASGM activities are characterized for producing less than 100 000 tons per year Run-of-Mine (ROM), and where the operation involves rudimentary techniques to extract the gold [13]. Additionally, because of the use of liquid mercury, gold mining is known not only to leave severe impacts in the altered landscapes, but also to be associated with human health impacts [14–17] and
social costs [17, 18]. Most of these ASGM activities are reported to be done illegally, although the Peruvian Government has been trying to implement new regulations and punitive campaigns against illegal miners [10, 11, 19, 20].

Understanding the drivers of deforestation is fundamental for the development of policies and measures to reduce greenhouse gas emissions from deforestation and for developing forest reference levels [21, 22] that will aid global initiatives such as REDD+ [23]. Moreover, indigenous communities and protected areas have proven to be important players in protecting the forests by reducing forest cover change and carbon emissions in the Amazon [24–26] and specifically in Madre de Dios [5, 27, 28]. Studies show gold mining-related forest loss inside the Tambopata National Reserve in Madre de Dios [10, 11], a protected area known to have high natural and culture value [29], and high biomass stocks [8], although there is disagreement as to the significance of mining-related deforestation within this protected area [11].

Therefore, this study uses satellite remote sensing for a spatial pattern analysis of forest loss from 2013 to 2018 in the Madre de Dios region to better understand land use land cover dynamics. While previous research has mapped gold mining-related deforestation, this paper includes additional analysis regarding rates and patterns of forest loss within and outside key land tenure areas such as Indigenous communities, the Tambopata National Reserve, mining concessions, and reforestation concessions, as well as evaluates the distribution of different drivers of forest loss to assess if other land uses rather than mining are causing significant forest loss in this region.

2. Methods

2.1. Study area

The study area is a 3500 km² subset of the Madre de Dios department of Peru, which is considered a region of global conservation significance [1] and a deforestation hotspot due to gold exploration [9–12]. This area is bordered to the north and west by the Inambari River, to the south by part of the Bahuaja-Sonene National Park, and to the east by part of the Tambopata National Reserve. The study area, shown in figure 1, contains large mining sites known as Guacamayo and La Pampa, as well as many ASGM sites. The Kotsimba indigenous community is located in the buffer zone of the protected areas, the Arazaire Indigenous community is located to the west of Kotsimba along with the Inambari River, and the Interoceanic Highway cuts through the study area.

2.2. Spatial features

Indigenous communities, national protected areas and their buffer zones, mining and reforestation concessions, rivers, and the Interoceanic Highway’s shapefiles were acquired from official national or regional sources (table 1) to perform a spatial pattern analysis of forest loss.

The Kotsimba Indigenous Community (316 km²), and the Arazaire Indigenous Community (13 km²) are legally recognized indigenous lands. National and International Laws concerning indigenous peoples’ rights in Peru give indigenous peoples a number of rights, including land rights, access to natural resources, and right to participate in decision-making processes. National and International Laws concerning indigenous peoples’ rights include: the Indigenous and Tribal Populations Convention, 1957 (ILO Convention No. 107); Law of native Communities and Promotion of Agriculture and Livestock Breeding in the Lower and Upper Rain-forest Regions, 1974 (Decree-Law 20653); Law of Native Communities and Agrarian Development in the Lower and Upper Rain-forest, 1978 (Decree-Law 22175); Indigenous and Tribal Peoples Convention, 1989 (ILO Convention No. 169); United Nations Declaration on Rights of Indigenous Peoples, 2007; Law of the Right to Prior Consultation with Indigenous or Native Peoples, 2011 (Law 29785).

The Tambopata National Reserve (193 km², within the study area) and the Bahuaja-Sonene National Park (420 km², within the study area) are National Protected Areas of Peru created, in 2000 and 1996 respectively, to conserve biodiversity and other associated values of cultural, scenic, and scientific interest, as well as for contribution of the sustainable development of Peru [30]. According to the Law of National Protected Areas of Peru (Law 26834), The Tambopata National Reserve falls into the category of ‘areas of direct use’, where the extraction of natural resources is permitted, primarily by the local population, and under a management plan. On the other hand, the Bahuaja-Sonene National Park falls into the category of ‘areas of indirect use’, where resources exploration is not permitted [31]. These protected areas have buffer zones that provide a transition between unprotected and protected areas and allow limited resource exploration mainly by indigenous communities [30].

The mining concessions allow the holders the right to explore and exploit mineral resources within the area covered by the concession, according to the General Mining Law (Supreme Decree No. 014–92–EM). The reforestation concessions were established within the framework of the Peruvian Forestry and Wildlife Law 27308 with the objective to promote, as a priority, afforestation and reforestation for production purposes, protection and environmental services, on lands with greater forest use capacity without vegetation cover or with scarce tree cover [32].
2.3. Satellite data and pre-processing

Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) Surface Reflectance Tier 1 products (path-row 03-69) from the dry season, July to September, were collected spanning 2013–2018. These products are readily available in the format of image collections on the Google Earth Engine (GEE) [33] platform used for this analysis. Landsat 7 and Landsat 8 granules were separated into different collections at first due to the difference in band designations (e.g.: RGB bands in Landsat 7 are bands 3, 2, 1, respectively, whereas in Landsat 8 they are bands 4, 3, 2, respectively). A cloud mask utilizing the Landsat quality assessment band was applied to mask clouds and cloud shadows of each scene in each collection. A shadow endmember of the spectral mixture analysis were further used to mask remaining cloud shadows. All the data acquisition and processing were done in GEE, and the accuracy assessment and creation of the final maps were done using ArcMap 10.6 [34].

2.4. Spectral mixture analysis

We used SMA to determine component parts of mixed pixels. A mixed pixel (r) can be described as a linear combination of spectral signatures of its endmembers, weighted by their sub-pixel fractional cover [35, 36].

\[ r = Mf + \epsilon \]

In equation (1), M is a matrix in which each column corresponds to the spectral signal of a specific endmember, and f is the column vector denoting the cover fractions occupied by each of the m endmembers in the pixel. The \( \epsilon \) is the portion of the spectrum that cannot be modeled using these endmembers (i.e. the residual).

To map gold mining-related deforestation in this region, using Landsat imagery and the Automated Monte Carlo Unmixing (AutoMCU) algorithm [37] within the Carnegie Landsat Analysis System lite (CLASlite) [38], Asner et al (2017) chose photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and bare substrate (S) as endmembers [10]. Similarly, Espejo et al (2018) used the same endmembers to map gold mining-related deforestation in this region [11], but using a fusion between CLASlite and the Global Forest Change dataset [39]. Bullock et al (2018) used the ‘unmix’ function embedded in GEE to map forest disturbances in the Brazilian Amazon from Landsat imagery using similar endmembers [40]. The GEE unmixing algorithm is a simple linear mixture model used to unmix each image with a single set of endmembers. Here, PV, NPV, S, water, and shadow were used as the spectral endmembers and we constrained the ‘unmix’ function within GEE to return endmember proportions that sum to one (i.e.
Table 1. Source of datasets.

| Data-shapefile                  | Source                                                                 | Last updated | Area (km²) | % of area of study |
|--------------------------------|------------------------------------------------------------------------|--------------|------------|--------------------|
| Mining concessions             | INGEMMET (Instituto Geologico Minero y Metalurgico)                    | 6/19/2018    | 1599       | 46%                |
| National protected areas (NPA) | SERNANP (Servicio National de Areas Naturales Protegidas por el Estado) | 2/8/2018     | 613        | 18%                |
| NPA buffer zone                | SERNANP                                                                | 6/11/2018    | 1068       | 31%                |
| Indigenous communities         | Amazonia SocioAmbiental/ Instituto del Bien Comun (IBC)                 | 12/2015      | 329        | 9%                 |
| Reforestation concessions      | SERFOR (Servicio Nacional Florestal y de Fauna Silvestre)               | 11/13/2017   | 729        | 21%                |
| Departments boundaries         | MINAM (Ministerio del Ambiente)                                       | N/A          | N/A        | N/A                |
| Interoceanic highway           | OpenStreetMap                                                          | 03/2019      | N/A        | N/A                |
| Rivers                         | Gobierno Regional Madre de Dios                                       | 5/23/2014    | N/A        | N/A                |
ignoring the error portion, forcing it to be 0) since it often results in physically meaningful estimates [41–44]. The reflectance values for each endmember were extracted from a single Landsat scene [43]. After the SMA algorithm was applied to each scene, the two collections were merged into a single collection. The resulting unmixed collection was then grouped by year and composited by the mean value into annual images. To remove the remaining cloud shadows on the unmixed composites, we masked the pixels that had a shadow fraction greater than 80%.

2.5. Change detection
There are conflicting definitions for the term deforestation. For example, the Forest and Agriculture Organization (FAO) defines deforestation as ‘the conversion of forest to another land use or the long term reduction of tree canopy below the minimum 10% threshold’ [45]. The Global Forest Observations Initiative (GFOI) implies that deforestation is interpreted as the processes leading to long-term loss of carbon that result in land-use change [46]. Here we use the term forest loss rather than deforestation to indicate a negative change in forest cover that resulted in land cover change. The change detection to indicate forest loss from 2013 to 2018 was based on a modified version of the deforestation algorithm used in the CLASlite software [38] where we use a decrease in the photosynthetic vegetation fraction greater or equal to 50% between a post image and a pre image to indicate forest loss. The final forest change map was composed by two classes: Forest Loss and No Forest Loss for our study period 2013–2018.

2.6. Accuracy assessment and identification of potential drivers
Planet Scope and RapidEye multispectral imagery were acquired through Planet [47] and used to validate the final map. The scenes were acquired for a coincident time period, from July to September for the years 2013 and 2018 covering the entire study area. For 2013, 20 scenes with 5 m resolution from RapidEye-1, RapidEye-2, RapidEye-3, and Rapid-Eye-5 were utilized, and for 2018, 46 scenes with 3 m resolution from Planet Scope were utilized. Following Olofsson et al. (2014), we employed a stratified random sampling design with proportional allocation (minimum of 150 points), yielding to 150 randomly generated points for the forest loss class and 950 randomly generated points for the no forest loss class [48]. Obvious classification errors were corrected prior to initiating the validation process as suggested by Olofsson et al. (2014) [48]. These errors were areas of forest loss that were easily identified as erroneous, such as areas in which we knew that the shadow and cloud masks were not able to mask appropriately the clouds and/or shadows, and areas alongside the rivers which change with time due to the morphology dynamics of these water bodies —river meanders. These erroneous areas (560 km²) represent less than 0.16% of the study area. Each point was visually interpreted as loss or no loss using the higher resolution imagery. Then, a confusion matrix was generated, yielding overall, producer’s, and user’s accuracies.

In order to identify potential drivers of forest loss, we simultaneously characterized each of the 150 forest loss points according to its apparent land cover/land use using the higher resolution imagery and the 2013–2016 Land use land cover dataset from the Peruvian Ministry of Environment [6]. The reference categories chosen for the land cover/land use were: Gold Mining, Agriculture/Pasture, River Flow, Urban, and Misclassified. The River Flow category represents areas of forest cover that were lost due to the natural flow of rivers (e.g. pixel was forest in 2013 but over the river in 2018). The Misclassified category represents the false positives of the forest loss class. The methodology is summarized in figure 2.

3. Results and discussions
Progression of forest loss can be observed in the results with concentrations revealed along the Malinowski River, within the Kotsimba community, on the north border of the Tambopata Reserve, and within the buffer zone of the protected areas (figure 3). The estimated areas of forest loss are presented in table 2: a total of 20,641 ha of forest cover has been lost from 2013 to 2018, with most of it (53%) being located within the buffer zone of the protected areas (10,860 ha). The average rate of loss is 4128 ha/yr, however an increase in annual rates is apparent, with 2017–2018 being the year of greatest loss (6076 ha) for the study area. The Kotsimba Indigenous Community, located inside of the buffer zone, also shows a higher rate of forest loss in recent years, 2017–2018, which is about 600 ha/yr, and corresponds to more than double that from 2013 to 2014. The areas of forest loss within this indigenous community are concentrated along a 1 km buffer of the Malinowski River which relates to ASGM activities [10]. The total area of forest loss within the Kotsimba community is approximately 2000 ha, corresponding to 6% of its total area, and to 9% of total loss of the study area. Within the protected areas, the total area of forest loss was 614 ha with the majority in the Tambopata Reserve (605 ha). Our results are in general agreement with Espejo et al. (2018), Miranda et al. (2016), and Vuohelainen et al. (2012); we find that even with a 123 ha/yr average rate of forest loss within the protected areas, the area of loss from 2013 to 2018 still represents only 3% of the total loss within our study area, and only 3% of the total protected area, suggesting that protected areas are effective in tempering deforestation rates [11, 27, 28].

Our results indicate that 49% of total forest loss areas lies outside of mining concessions’ locations
Figure 2. Workflow of methodology employed in this study.

Figure 3. Forest loss progression in the study area from 2013 to 2018.
which suggests that could be linked to illegal gold mining activities, or other causes, such as urbanization, agriculture, logging, and cattle ranching. A vast extent of forest loss within the Kotsimba community (1510 ha, or 77%) and within the Tambopata Reserve (443 ha, or 73%) also falls outside mining permits. A large amount of forest loss (4976 ha) happened within reforestation concessions, and, in many cases, the reforestation concessions overlapped with mining concessions. In these areas of overlap, we observed a total loss of 1960 ha from 2013 to 2018, which corresponds to 9% of total loss in the study area.

### Table 2. Annual forest loss (ha) per feature from 2013 to 2018.

| Features/Years                      | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | Average rate | Total% Total 
|-------------------------------------|-------|-------|-------|-------|-------|-------|---------------|---------------- |
| Outside mining concessions          | 1650  | 1492  | 1628  | 2154  | 3235  | 2032  | 10 159        | 49%   |
| Inside mining concessions           | 1688  | 1988  | 1755  | 2210  | 2841  | 2096  | 10 482        | 51%   |
| Areas where mining and reforestation concessions overlap | 118   | 280   | 367   | 684   | 511   | 392   | 1960         | 9%    |
| Inside reforestation concessions    | 769   | 598   | 827   | 1402  | 1380  | 995   | 4976         | 24%   |
| Kotsimba indigenous community      | 216   | 385   | 298   | 479   | 574   | 390   | 1952         | 9%    |
| Arazaire indigenous community      | 35    | 22    | 17    | 13    | 20    | 21    | 107          | 1%    |
| Total indigenous communities       | 231   | 407   | 315   | 492   | 594   | 412   | 2059         | 10%   |
| Buffer zone                         | 1811  | 1838  | 1588  | 2268  | 3355  | 2,172 | 10 860       | 53%   |
| Tambopata national reserve         | 48    | 9     | 379   | 130   | 39    | 121   | 605          | 3%    |
| Bahuaja-Sonene National Park       | 3     | 1     | 0     | 1     | 4     | 2     | 9            | 0%    |
| Total protected areas              | 51    | 10    | 379   | 131   | 43    | 123   | 614          | 3%    |
| Study area                          | 3338  | 3480  | 3383  | 4364  | 6076  | 4,128 | 20 641       | 100%  |

(figure 4; table 2), which suggests that could be linked to illegal gold mining activities, or other causes, such as urbanization, agriculture, logging, and cattle ranching. A vast extent of forest loss within the Kotsimba community (1510 ha, or 77%) and within the Tambopata Reserve (443 ha, or 73%) also falls outside mining permits. A large amount of forest loss (4976 ha) happened within reforestation concessions, and, in many cases, the reforestation concessions overlapped with mining concessions. In these areas of overlap, we observed a total loss of 1960 ha from 2013 to 2018, which corresponds to 9% of total loss in the study area.
—relatively small compared to locations where these concessions do not overlap (51% mining concessions only; 24% reforestation concessions only). Anderson et al. (2018) states that due to lack of coordination, the distinct government agencies in Peru allocate the same land for different uses but this is primarily assumed to be unintentional, and even if intentional, it is presumed to cause no conflict [49]. Gutierrez-Velez et al. (2011) observed that companies that intend to expand their palm oil plantations in Peru, seek to do so in areas that have not been assigned any other use to avoid conflict [50]. Therefore, we believe that the lower rates of forest loss in cases of overlapping land allocations in this region could also be a conflict avoidance strategy between land users, and that these overlapping allocations could be used as a policy tool for conservation [49].

The overall accuracy for the analysis outlined here was 96%, with a confusion matrix shown in Table 3. After characterizing the 150 forest loss sample points, we found that 67 points (45%) were related to gold mining, 57 points (38%) were related to agriculture and/or pastures, 4 points (3%) were related to the natural rivers’ flow, and 21 points (14%) were forest loss false positives. This confirms that gold mining was the leading cause of forest loss in the region [11] from 2013 to 2018, but also shows that agriculture/pasture areas have a major contribution on driving forest loss. By analyzing the nearest distance to the different spatial features (Table 4) and taking the median value for the forest sample points characterized as gold mining and agriculture/pasture (Table 4), we found that gold mining activities occur closer to indigenous communities, protected areas and their buffer zone compared to agriculture/pasture fields; whereas for the Interoceanic Highway, rivers, and mining concessions, agriculture/pasture fields appear to be more predominant than gold mining activities. Therefore, we suggest that gold mining activities are the main cause of forest loss within the buffer zone (0.0 km median

### Table 3. Confusion matrix and accuracy assessment.

| Sample points (#) | Forest loss-reference | No forest loss-reference | Map totals |
|-------------------|-----------------------|--------------------------|------------|
| Forest loss-map   | 129                   | 21                       | 150        |
| No forest loss-map| 28                    | 922                      | 950        |
| Reference totals  | 157                   | 943                      | 1100       |

| Area proportions (%) | Forest loss-reference | No forest loss-reference | Map totals |
|----------------------|-----------------------|--------------------------|------------|
| Forest loss-map      | 0.0540                | 0.0088                   | 0.0628     |
| No forest loss-map   | 0.0276                | 0.9096                   | 0.9372     |
| Reference totals     | 0.0816                | 0.9184                   | 1          |

| User’s accuracy       | 86%                   | 97%                      |
| Producer’s accuracy   | 66%                   | 99%                      |
| Overall accuracy      | 96%                   |                          |

### Table 4. Median distance and percentage of forest loss sample points to spatial features (N/A: The Interoceanic highway and rivers were not included in the analysis since they represent polyline features).

| Potential drivers | Gold mining |
|-------------------|-------------|
| Indigenous communities | 68.7        | 132.2        |
| Protected areas   | 56.8        | 220.6        |
| Buffer zone       | 0.0         | 58.2         |
| Interoceanic highway | 104.5      | 59.7         |
| Rivers            | 6.8         | 5.2          |
| Mining concessions | 9.1         | 0.0          |
| Reforestation concessions | 12.1     | 12.6         |

| % of points inside | Gold mining |
|--------------------|-------------|
| Indigenous communities | 24%        | 2%           |
| Protected areas   | 7%          | 0%           |
| Buffer zone       | 85%         | 26%          |
| Interoceanic highway | N/A        | N/A          |
| Rivers            | N/A         | N/A          |
| Mining concessions | 18%         | 75%          |
| Reforestation concessions | 33%     | 21%          |
nearest distance), and agree with Swenson et al (2011) that these activities occur independently of roads (104.5 km median nearest distance) [9]. Although agriculture and cattle ranching show a comparatively high median nearest distance to the Interoceanic Highway (59.7 km), we recognize that this could be due to the lack of a secondary roads dataset for this research. Moreover, similarly to Asner et al (2017), we find that it is difficult to explain reasons behind inter-annual changes in rate of forest loss [10], but agree with Espejo et al (2018) that the completion of the Interoceanic Highway, and the consequent increase in secondary roads network, helped the increase of forest loss rates over time [11]. Moreover, it is well-documented that the presence of roads is directly related to deforestation activities around the world [51–54].

4. Conclusion

The region of Madre de Dios has been and continues to be an extractive frontier to be occupied and exploited for many years now besides its exceptionally rich concentration of endemic species. We demonstrated that from 2013 to 2018, 20 641 hectares of forest have been lost where the majority is within the buffer zone of national protected areas. In addition, gold mining seems to be the main driver of forest loss but agriculture and cattle ranching are also responsible for forest cover change. These results are in agreement with other related studies that show an increase in rates of deforestation in the Amazon: Junior and Lima (2018) estimated an increase in the deforestation rate from 2009–2012 to 2013–2016 of approximately 49% in the Amazonian biome of Mato Grosso, Brazil, an extractive frontier primarily characterized by forest cover change due to soy plantations and pasture, rather than mining [55]; Cabrera et al (2019) also show increase in mining-related deforestation from 2014 to 2015 in extractive frontiers of Colombia [56].

The Peruvian government has been trying to control the growth of illegal gold mining activities in this region through the implementation of legal decrees and police interventions. Most recently, the Mercury Operation, an intervention managed by the Peruvian Ministry of Interior that took place in La Pampa from February to May of 2019 to eradicate the illegal mining activities detained 152 people. The Monitoring of the Andean Amazon Project (MAAP) has contributed to a decrease of 92% (2018–2019) in gold mining-related deforestation in this region [12]. Furthermore, these law enforcement actions have proven to be effective in reducing deforestation in other countries such as Brazil, which reduced deforestation in the Amazon in 84% from 2004 to 2012 [57, 58]. Thus, we believe that these actions are crucial for conservation success across the diverse frontier landscapes in this region.

Conservation areas in this region play an important role in tempering forest loss since the area of forest loss inside the Tambopata Reserve represents only 3% of total forest loss in the study area, and inside the Kotsimba Indigenous Community 6%. Systematic monitoring of forest cover change and the understanding of its underlying causes is valuable for a better sustainable land management, and for a long-term socio-economic development of the region. This study underlines the fact that progressive forest loss expansion continues to prevail in this region. The use of a cloud-computing platform for accessing and processing time-series data is promising and the use of SMA as a change detection technique provide accurate results.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The Google Earth Engine code can be accessed at https://code.earthengine.google.com/ac0a4d1d72197a0fd3a26ffbf5da5cc2.

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References

[1] Myers N, Mittermeier R A, Mittermeier C G, da Fonseca G A B and Kent J 2000 Biodiversity hotspots for conservation priorities Nature 403 853–8
[2] Peru. Peruvian Law 26311. Declaran Capital de La Biodiversidad del Peru al Departamento de Madre de Dios, 1994 (http://leyes.congreso.gob.pe/Documentos/Leyes/26311.pdf)
[3] Alvarez N L and Naughton-Treves L 2003 Linking national agrarian policy to deforestation in the Peruvian Amazon: a case study of Tambopata, 1986–1997 Ambio 32 269–74
[4] Chavez A B and Perz S G 2012 Adoption of policy incentives and land use: lessons from frontier agriculture in southeastern Peru Human Ecology 40 525–39
Environ. Res. Lett. 14 (2019) 124045

[5] Scullion J J, Vogt K A, Sienkiewicz A, Gmur S J and Trujillo C J 2014 Assessing the influence of land-cover change and conflicting land-use authorization on ecosystem conservation on the forest frontier of Madre de Dios, Peru Biol. Conservation 171 247–58

[6] MINAM. Geobosques: Plataforma de Monitoreo de Cambios sobre la Cobertura de los Bosques. Ministerio del Ambiente, 2017 (http://geobosques.minam.gov.pe/geobosque/view/index.php)

[7] Naughton-Treves L 2004 Deforestation and carbon emissions at tropical frontiers: a case study from the Peruvian Amazon World Dev. 32 173–90

[8] Asner G P et al 2010 High-resolution forest carbon stocks and emissions in the Amazon Proc. Natl Acad. Sci. 107 16738–42

[9] Swenson J S, Carter C E, Domes J C and Delgado C J 2011 Gold mining in the Peruvian Amazon: global prices, deforestation, and mercury imports PLoS One 6 e18875

[10] Asner G P and Tuppyach R 2017 Accelerated losses of protected forests from gold mining in the Peruvian Amazon Environ. Res. Lett. 12 090044

[11] Espejo J C, Messinger M, Roman D F, Ascorra C and Luis E M 2018 Deforestation and forest degradation due to gold mining in the Peruvian Amazon: a 34-year perspective Remote Sens. 10 1–12

[12] MAAP. Monitoring of the Andean Amazon Project, 2019 (https://maapproject.org/about-maap/)

[13] Seccatore J, Veiga M, Orioligasso C, Marin T and De Tomi G A 2014 An estimation of the artisanal small-scale production of gold in the world Sci. Total Environ. 496 662–7

[14] Ashe K 2012 Elevated mercury concentrations in humans of madre de dios, Peru PLoS One 7 e33805

[15] Yard E E, Horton J, Schier J G, Caldwell K, Sanchez C, Lewis L and Gastañaga C 2012 Mercury exposure among artisanal gold miners in Madre de Dios, Peru: a cross-sectional study J. Med. Toxicol. 8 441–8

[16] Diringer S, Feingold B J, Ortiz E, Gullis J, Arauido-Flores J M, Berky A, Pan W K Y and Hus K-H 2015 River transport of mercury from artisanal and small-scale gold mining and risks for dietary mercury exposure in Madre de Dios, Peru Environ. Sci. Process. Impacts 17 478–87

[17] Kahhat R, Parodi E, Larrea-Gallegos G, Mesta C and Vázquez-Rowe I 2019 Environmental impacts of the life cycle of alluvial gold mining in the Peruvian Amazon rainforest Sci. Total Environ. 662 940–51

[18] Rivera E V 2014 Implicancias de la minería informal sobre la salud de mujeres y niños en Madre de Dios Sociedad Peruana de Derecho Ambiental C D Cheek and I Valencia (Lima: Sociedad Peruana de Derecho Ambiental) (http://actualidadambiental.pe/wp-content/uploads/2014/11/Estudio-sobre-la-mineria-ilegal-y-su-implicancia-en-la-salud-de-Madre-Dios.pdf)

[19] Salo M, Hiedanpää J, Karlsson T, Avila L C, Kotelainen J, Jounela P and Garcia R G 2016 Local perspectives on the formalization of artisanal and small-scale mining in the Madre de Dios gold fields, Peru Extractive Ind. Soc. 3 1058–66

[20] Kolen J, de Theije M and Mathis A 2013 Formalized small-scale gold mining in the brazilian amazon: an activity surrounded by informality (Amsterdam: CEDLA) (http://cedla.uva.nl/50_publications/pdfs/ cuadernos/ cuad26.pdf) (page = 15)

[21] Hosonuma N, Herold M, De Sy V, De Fries R S, Brockhaus M, Verchot L, Angelsen A and Romijn E 2012 An assessment of deforestation and forest degradation drivers in developing countries Environ. Res. Lett. 7 044009

[22] Kissinger G, Herold M and De Sy V 2012 Drivers of deforestation and forest degradation A Synthesis Report for REDD + Policymakers. Technical Report (Vancouver: LexemeConsulting)

[23] UNFCCC 2013 Report of the conference of the parties on its nineteenth session, held in Warsaw from 11 to 23 November 2013 Technical Report (New York: United Nations)

[24] Asner G P, Martin R E, Tuppyach R and Laetayo W 2017 Conservation assessment of the Peruvian Andes and Amazon based on mapped forest functional diversity Biol. Conservation 210 80–8

[25] Nolte C, Agrawal A, Silivus K M and Soares-Filho B S 2013 Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon Proc. Natl Acad. Sci. 110 4956–61

[26] Blackman A and Veit P 2018 Titled Amazon indigenous communities cut forest carbon emissions Ecol. Econ. 133 56–67

[27] Vuohelainen A J, Coad L, Marshews T R, Malhi Y and Killeen T J 2012 The effectiveness of contrasting protected areas in preventing deforestation in Madre de Dios, Peru Environ. Manag. 50 645–63

[28] Miranda J J, Corral L, Blackman A, Asner G and Lima E 2016 Effects of protected areas on forest cover change and local communities: evidence from the Peruvian Amazon World Dev. 78 288–307

[29] Torres-Sovero C, González J A, Martín-López B and Kirkby C A 2012 Social-ecological factors influencing tourist satisfaction in three ecotourism lodges in the southeastern Peruvian Amazon Tourism Manage. 33 445–52

[30] SERNANP. Servicio Nacional de Areas Naturales Protegidas por el Estado, 2018 (http://sernanp.gob.pe/)

[31] 1997 Peru. Peruvian Law of National Protected Areas. Ley No 26834, Diario Oficial El Peruano 6215, 130721–130752, 1997 (Lima, Peru: Congreso de La Republica) (http://leyes.congreso.gob.pe/Documentos/Leyes/26834.pdf)

[32] Peru. Peruvian Law for Forestry and Wildlife. Ley No 27308. Diario Oficial El Peruano 7328, 190283–190289, 2000 (Lima, Peru: Congreso de La Republica) (www.leyes.congreso.gob.pe/Documentos/Leyes/27308.pdf)

[33] Vázquez-Rowe I, Hancher M, Dixon M, Byushchenko S, Thau D and Moore R 2017 Google earth engine: planetary-scale geospatial analysis for everyone Remote Sens. Environ. 202 18–27

[34] ESRI 2011 ArcGIS Desktop: Release 10 (Redlands, CA: Environmental Systems Research Institute)

[35] Wilkantika K, Uchida S and Yamamoto Y 2002 Mapping vegetable area with spectral mixture analysis of the Landsat-ETM IEEE Int. Geoscience and Remote Sensing Symp. vol 4, pp 1965–7

[36] Adams J B, Smith M O and Johnson P E 1986 Spectral mixture modeling: a new analysis of rock and soil types at the viking lander 1 site J. Geophys. Res. 91 8098

[37] Asner G P and Heidebrecht K B 2002 Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: comparing multispectral and hyperspectral observations Int. J. Remote Sens. 23 3939–58

[38] Asner G P 2009 Automated mapping of tropical deforestation and forest degradation: CLASLite J. Appl. Remote Sens. 3 033543

[39] Hansen M C et al 2013 High-resolution global maps of 21st-century forest cover change Science 342 850–3

[40] Bullock E L, Woodcock C E and Olofsson P 2018 Monitoring tropical forest degradation using spectral unmixing and Landsat time series analysis Remote Sens. Environ. (accepted) (https://doi.org/10.1016/j.rse.2018.11.011)

[41] Adams J B, Smith M O and Gillespie A R 1993 Imaging vegetation with spectral mixture analysis of the Landsat-ETM IEEE Trans. Geosci. Remote Sens. 31 1079–93

[42] Baldeck G, Roberts D A and de Figueiredo Ribeiro F 2019 Spectral mixture analysis in Google Earth Engine to model and delineate fire scars over a large extent and a long-time-series in a rainforest–savanna transition zone Remote Sens. Environ. 232 111340
[45] FAO 2015 Forest resources assessment 2015: terms and definitions. FAO Report Forest Resources Assessment Working Paper 180 (Rome: Food and Agriculture Organization) (http://fao.org/3/a-ap662e.pdf)

[46] GFOI 2016 Integrating remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest. Edn 2.0 (Rome: Group on Earth Observations Observations Initiative) (https://fs.fed.us/nrs/pubs/jrnl/2016/nrs_2016_penman_001.pdf)

[47] Planet Team 2017 Planet Application Program Interface: In Space for Life on Earth. (San Francisco, CA: Planet Team) (https://api.planet.com/)

[48] Olofsson P, Foody G M, Herold M, Stehman S V, Woodcock C E and Wulder M A 2014 Good practices for estimating area and assessing accuracy of land change Remote Sens. Environ. 148 82–57

[49] Anderson C M, Asner G P, Llactayo W and Lambin E F 2018 Overlapping land allocations reduce deforestation in Peru Land Use Policy 79 174–8

[50] Gutiérrez-Vélez V H and DeFries R 2013 Annual multiresolution detection of land cover conversion to oil palm in the Peruvian Amazon Remote Sens. Environ. 129 154–67

[51] Liu D S, Iverson L R and Brown S 1993 Rates and patterns of deforestation in the Philippines: application of geographic information system analysis Forest Ecol. Manage. 57 1–16

[52] Cropper M, Puri J and Griffiths C 2001 Predicting the location of deforestation: the role of roads and protected areas in North Thailand Land Econ. 77 172–86

[53] Busch J and Ferretti-Gallon K 2017 What drives deforestation and what stops it? A meta-analysis Rev. Environ. Econ. Policy 11 3–23

[54] Phompila C, Lewis M, Ostendorf B and Clarke K 2017 Forest cover changes in lao tropical forests: physical and socio-economic factors are the most important drivers Land 6 23

[55] Silva C A and Lima M 2018 Soy Moratorium in Mato Grosso: deforestation undermines the agreement Land Use Policy 71 540–2

[56] Cabrera E et al 2019 Colombian forest monitoring system: assessing deforestation in an environmental complex country Deforestation Around the World (Rijeka: InTech)

[57] 2018 INPE. Projeto PRODES: Monitoramento da Floresta Amazônica Brasileira por Satélite (Brazil: Instituto Nacional de Pesquisas Espaciais) (http://obt.inpe.br/OBT/assuntos/programas/amazonia/prodes)

[58] Tacconi L, Rodrigues R J, Maryudi A and Muttaqin M Z 2019 Law enforcement and deforestation: lessons for Indonesia from Brazil Forest Policy Econ. 108 101943