MAPPING DISTURBANCE FROM SELECTIVE LOGGING IN TROPICAL FORESTS OF THE YUCATAN PENINSULA, MEXICO †

[MAPEO DEL DISTURBIO POR LA TALA SELECTIVA EN BOSQUES TROPICALES DE LA PENÍNSULA YUCATÁN, MÉXICO]

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SUMMARY

Background. Mapping selective logging impacts on the Yucatan Peninsula is important to pursuing carbon emissions reduction and biodiversity conservation goals. **Objective.** To evaluate the effectiveness of applying remote sensing techniques using LANDSAT 8 OLI imagery to detect tropical forest disturbance from timber harvesting in four communally managed forests (*ejidos*). We further assess differences among them in terms of implementing improved forest management (IFM) and reduced impact logging (RIL). **Methodology.** Vegetation indices were calculated, and forest cover classification was performed to map logged and unlogged forest and specific harvest disturbances (e.g. felling gaps, skid trails, logging roads and log landings) in annual cutting areas of 2014. Accuracy assessments were conducted based on validation points collected in the field after logging. **Results.** We found that 75% of the binary classifications (logged and unlogged forest) had mean overall accuracies greater than 60%, representing a fair (40 to 70%) accuracy, although mapping of specific harvesting disturbances had poor accuracy (<40%). Vegetation indices that performed the best were normalized vegetation index (NDVI), Tasseled Cap Greenness and Tasseled Cap Wetness. Ejidos that applied IFM and RIL impacted a smaller percentage of their cutting areas and less area of forest per cubic meter of timber extracted, despite similar or higher logging intensities than ejidos without improved practices. **Implication.** Monitoring selective logging disturbance is important to improved forest management and certification of sustainability. **Conclusion.** Mapping and monitoring impacts from selective logging by forest managers and technicians can be performed in a cost-efficient manner using LANDSAT 8 images, although accuracy could be improved with higher resolution imagery.
Key words: Selective logging, LANDSAT 8 OLI, harvest impacts, Yucatan Peninsula, reduced impact logging.

RESUMEN

Antecedentes. El mapeo de los impactos de la tala selectiva en la Península de Yucatán es importante para lograr la reducción de las emisiones de carbono y los objetivos de conservación de la biodiversidad. **Objetivo.**

† S*ubmitted August 8, 2019 – Accepted October 16, 2019.*
ISSN: 1870-0462.

Evaluar la efectividad de la aplicación de técnicas de teledetección mediante el uso de imágenes LANDSAT 8 OLI para detectar la perturbación del bosque tropical a partir de la extracción de madera en cuatro bosques con manejo comunitario (ejidos). Además, evaluamos las diferencias entre ellos en términos de implementación de manejo forestal mejorado (IFM) y prácticas de aprovechamiento de impacto reducido (RIL). **Metodología.** Se calcularon los índices de vegetación y se realizó la clasificación de la cubierta forestal para hacer un mapa de las zonas taladas y no taladas y las perturbaciones específicas del aprovechamiento (por ejemplo, claros por la tala de árboles, carriles de arrastre, caminos forestales y áreas de acopio de madera) en las áreas de corta anual de 2014. Las evaluaciones de precisión se realizaron en función de los puntos de validación colectados en el campo después del aprovechamiento. **Resultados.** Encontramos que el 75% de las clasificaciones binarias (áreas impactadas y no impactadas) tenían precisiones globales medias superiores al 60%, lo que representa una precisión aceptable (40 a 70%), aunque el mapeo de las perturbaciones específicas de la cosecha tuvo poca precisión (<40%). Los índices de vegetación que obtuvieron los mejores resultados fueron el índice de vegetación de diferencia normalizada (NDVI), Tasseled Cap Greenness y Tasseled Cap Wetness. Los ejidos que aplicaron IFM y RIL impactaron un porcentaje menor de sus áreas de corta y menos área de bosque por metro cúbico de madera extraída, a pesar de intensidades de tala similares o mayores que los ejidos sin prácticas mejoradas. **Implicaciones.** El monitoreo del impacto por la tala selectiva es importante para mejorar el manejo forestal y la certificación de sostenibilidad. **Conclusiones.** El mapeo y el monitoreo de los impactos de la tala selectiva por gestores y técnicos forestales se puede realizar de manera costo-efectiva utilizando imágenes LANDSAT 8, aunque la precisión se puede mejorar con imágenes de alta resolución.

Palabras clave: Tala selectiva, LANDSAT 8 OLI, impactos de la cosecha, Península de Yucatán, tala de impacto reducido.

INTRODUCTION

On the Yucatan Peninsula, forestry is conducted by selective logging which involves the harvesting of commercially valuable timber present at very low densities in the forest (1-20 trees·ha^{-1}) (Petrokofsky *et al.*, 2015). Cutting cycles of selective silvicultural systems are around 25 years, presumably allowing forest disturbance from logging to recover by natural regeneration and enrichment planting (Navarro-Martínez *et al*., 2017; Ellis *et al.*, 2015). However, disturbance from selective logging can lead to forest degradation when there is a reduction in the capacity of the ecosystem to supply goods and services (FAO, 2010). Added to deforestation, degradation makes up a significant source (20%) of carbon emissions from tropical forests which can eventually result in deforestation (Griscom et al., 2009). In the tropics, poor forest management and logging practices (Pearson *et al.*, 2017), in addition to illegal logging (Vaglio *et al.*, 2016), are major causes of forest degradation. However, sustainable forestry, through improved forest management (IFM) and reduced impact logging (RIL), has been identified as a viable method to conserve forest carbon stocks and reduce emissions (Putz *et al.*, 2008).

For decades, communally managed landholdings with forests (*ejidos*) on the Yucatan Peninsula have played a significant role in producing timber, supporting rural livelihoods and conserving natural resources. Several studies have shown how community forest management in the region has aided in reducing deforestation and maintaining forest cover (Ellis and Porter, 2008; Bray *et al.* 2004), while improving the economic well-being of ejidos through timber revenues (Antinori and Bray, 2005). Thus, both national and international efforts have been underway to strengthen and promote community forest management as a "climate smart" land use that also helps conserve biodiversity (CONAFOR, 2015; UN-REDD Programme, 2015). Specifically, RIL, which includes a wide range of improved forestry practices including directional felling, alternative log extraction (skidding) methods, and skid trail and road planning (Read, 2003), has already shown potential to reduce forest disturbance and carbon emissions from selective logging activities (Ellis *et al.* 2019).

Currently, REDD+ (Reduction of Emissions from Deforestation and Degradation) strategies on the Yucatan Peninsula are focusing on reducing carbon emissions and biodiversity impacts from forestry operations through IFM and RIL, and at the same time, increasing timber production, strengthening community forest enterprises, improving timber markets, and promoting sustainable forestry certification (e.g. Forest

Stewardship Council, FSC) (Herold and Skutsch, 2011). As a result, there is a recent and growing need to develop time and cost-efficient methods to map and monitor forest disturbance (and recovery) caused by selective logging and assess impact reductions from applying IFM and RIL practices (Asner *et al.*, 2005).

Remote sensing is a potential tool for forest managers and technicians to rapidly and cheaply assess and map disturbance from selective logging in tropical forests (Asner *et al*. 2002). Nevertheless, forest disturbance from this activity occurs at a finer scale than other types of anthropogenic or natural disturbances, making it a challenging task for the spatial resolution of commonly available satellite imagery, such as LANDSAT. Also, cloud free images in tropical regions are often limited. As would be expected, some studies show that remote sensing techniques using high resolution imagery, such as IKONOS (Read, 2003) and LIDAR (Asner *et al.*, 2010), enhance the detection of disturbed forest by selective logging compared to using LANDSAT only. However, less accessibility and much higher cost of high-resolution imagery and LIDAR data limit its use by forest technicians and managers. Moreover, on the Yucatan Peninsula, remote sensing techniques have not been evaluated and much less implemented in forest management.

Even though suboptimal results have been obtained using LANDSAT to detect forest disturbance from logging (Read, 2003), other studies have demonstrated its potential in temperate (Hais *et al.*, 2009) and tropical forest (Monteiro *et al*., 2003). The earliest uses of LANDSAT to map selective logging impacts in tropical forest relied on visual interpretation, which proved problematic especially when harvest intensities were low (Souza and Barreto, 2000). Image processing such as maximum likelihood classifiers and spectral mixture analysis (SMA) of pixels (end member fractions) were later used to detect and map selectively logged areas in tropical forest using LANDSAT and ASTER imagery (Broadbent *et al.*, 2006). Use of different vegetation indices such as NDVI, NDMI, Tasseled Cap (wetness, brightness and greenness) and other derived disturbance indices (DI) have also been applied to detect forest disturbance from logging (Hais *et al.*, 2009). Currently, LANDSAT has been used to map degradation by logging and other activities in Brazil, Perú and Madagascar using the CLASlite (Carnegie Landsat Analysis System) automated system based on SMA of photosynthetic and non-photosynthetic vegetation within image pixels (Bryan *et al.*, 2013). However, for our study area on the Yucatan Peninsula the CLASlite automated system did not show promising outcomes in detecting forest disturbance from selective logging (Hernández Gómez *et al*., 2019).

Integration of remote sensing methods to monitor and quantify forest impacts from selective logging operations are beneficial to efforts in obtaining management authorization, financial support and certification of sustainability (e.g. Forest Stewardship Council, FSC). The objective of this research was to evaluate the effectiveness of using LANDSAT 8 OLI derived vegetation indices (e.g. NDVI and Tasseled Cap) to detect and map forest disturbance from selective logging in four ejido harvest areas on the Yucatan Peninsula. We evaluated LANDSAT since they are a free and openly available image archive with potential for identifying forest disturbance and degradation from a variety of human and natural impacts including logging (Jarron *et al.*, 2017). Furthermore, we apply techniques that are user-friendly and commonly available in most remote sensing and GIS software, some of them open access (e.g. GRASS, ILWIS, QGIS), facilitating its application by local forest managers and technicians. We compared and discuss forest disturbance from selective logging in relation to differences in the implementation of RIL practices and other forest management characteristics among the study ejidos. Finally, we offer conclusions and recommendations on using LANDSAT 8 OLI imagery for monitoring disturbance and degradation impacts from selective logging, which up to date has not been evaluated on the Yucatan Peninsula.

MATERIALS AND METHODS

Study Sites. Forest disturbance from selective logging was analyzed in four ejidos in the Selva Maya region of Quintana Roo, Mexico (Figure 1). Climate is warm and subhumid, with mean annual precipitation of 1200 mm and a marked dry season (< 60 mm of rainfall per month) from November to April. Altitude varies from 10 to 70 m.a.s.l., with maximum elevations at the southern and western portion of the study area reaching 300 m.a.s.l. (Ellis and Porter-Bolland, 2008). The predominant vegetation is sub-evergreen tropical forest, characterized by a tree canopy height between 15 and 25 m, of which 25% lose their leaves during the dry season. Common tropical forest trees are big leaf mahogany (*Swietenia macrophylla*), sapodilla or chicle (*Manilkara zapota*) and Maya nut or ramón (*Brosimum alicastrum*) (Ellis *et al.*, 2017). Forest types are related to soils and topography; upland forests are located on high ground over well-drained rendzinas, and lowland forests in flooded depressions with gleysols and vertisols (Toledo-Aceves *et al.*, 2009).

The four community forestry ejidos analyzed in this study are Noh Bec, Nueva Guadalajara, Felipe Carrillo Puerto and Santa Maria Poniente (Figure. 1). These ejidos make regular use of their forest areas for commercial timber harvesting and have authorized forest management plans that apply a polycyclic selective sylvicultural system with 25-year cutting cycles (Bray *et al.*, 2004). Forestry ejidos typically have a permanent management area that ranges from 800 ha to 40,000 ha, divided into annual cutting areas (ACA) that range from 200 ha to 2800 ha. Large ACAs are sub-divided into smaller management units that are typically 100 ha. Within the ACA, trees to be felled are marked, cut and extracted using a skidder (articulated forestry tractor) that drags the timber to small log landings that vary in size from 400 to 1200 m^2 (Arevalo *et al.*, 2016), locally known as "bacadillas". Subsequently, the logs are collected from the log landings which are accessed by logging roads, and then transported to nearby sawmills for processing and commercialization. Timber harvesting operations in these ejidos are typically conducted from January to May before the rainy season.

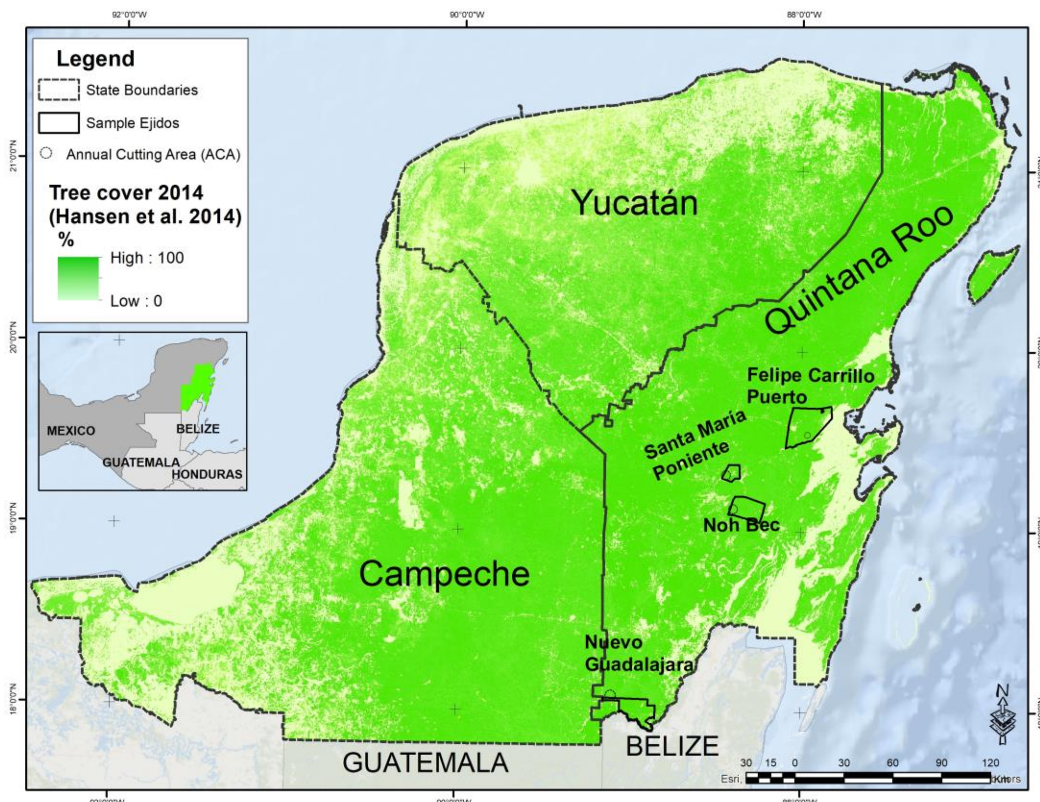

Figure. 1. Location of study area and forestry ejidos on the Yucatan Peninsula.

Table 1. Description of the four-community forestry ejidos sampled for mapping selective logging forest disturbance on the Yucatan Peninsula.

Ejido	Ejido area ha	Forest area ha	Size ACA ha (MU)	Implementation of IFM and RIL	Harvest Volume from ACA (Logging Intensity)
Felipe Carrillo Puerto	47, 223	24,780	1,843 (50)	Without IFM and RIL	1,621 $m^3 \cdot yr^{-1}$ (1 $m^3 \cdot ha^{-1}$)
Noh Bec	24,122	18,000	1,008 (25)	FSC certified with IFM and RIL implementation (e.g. harvest planning and directional felling)	7,000 $m^3 \cdot yr^{-1}$ (7 $m^3 \cdot ha^{-1}$)
Santa María Poniente	8,544	5,000	200	Without IFM and RIL	700 $m^3 \cdot y^{-1}$ 3 $m^3 \cdot ha^{-1}$
Nuevo Guadalajara	28,279	12,234	240	Implements RIL (e.g. modified agricultural tractor for skidding)	500 $m^3 \cdot y^{-1}$ 3 $m^3 \cdot ha^{-1}$

The four ejidos sampled in this study vary in their forest management characteristics and practices (Table 1). Noh Bec, for example, is certified by the Forest Stewardship Council (FSC) and implements IFM and RIL practices. IFM refers to multiple objective forestry that aims to achieve sustainable production, in addition to biodiversity conservation and providing environmental services (Griscom and Cortez, 2013), while RIL specifically implies practices that reduce forest impacts during planning and harvesting operations (Ellis *et al*., 2019; Asner *et al.*, 2010; Griscom *et al.*, 2009; Putz *et al*., 2008) such as skid trail planning, to improve harvest efficiency, and directional felling, to reduce harvest impacts. Moreover, they are an ejido with a large ACA (1008 ha) that harvests a larger annual volume of timber in comparison to the other ejidos, having the highest harvest intensity in their ACA (7 $m^3 \cdot ha^{-1}$). Nueva Guadalajara is an ejido that also implements RIL practices such as the use of a modified agricultural tractor to extract logs, instead of a forestry skidder which are larger, wider and heavier, causing more damage to forest vegetation. However, forestry operations in Nueva Guadalajara are of a smaller scale, having a small ACA (240 ha) and lower harvest intensity (3 $m^3 \cdot ha^{-1}$) compared to Noh Bec.

Calculation of Vegetation Indices. We apply basic remote sensing techniques to map forest disturbance from selective logging in the 2014 ACAs. Vegetation indices are calculated for each ACA using post-harvest LANDSAT 8 OLI images from December 2014. The month of December was optimal to evaluate disturbance from selective logging being at the end of the year after all logging has been completed and right before the next logging season begins. The LANDSAT 8 OLI images used in the study were path-row 19-47 for Felipe Carrillo Puerto, Noh Bec, Santa María Poniente and path-row 19-48 for Nueva Guadalajara. All images were obtained from Global Viewer of the US Geological Survey (USGS) in Level 1 format which are topographically calibrated and geometrically corrected (https://landsat.usgs.gov/landsat-processing-details).

Prior to calculating the vegetation indices and for purposes of radiometric and atmospheric correction, DN (digital number) values for each image were converted to radiance values and these subsequently converted to surface reflectance using raster calculator tool of ArcGis 10.3 and following the methodology and step by step guide provided by Grind GIS: http://grindgis.com/blog/vegetation-indices-arcgis#1. Subsets of each ejido territory were then made from the LANDSAT scenes and the following five vegetation-disturbance indices were calculated using raster calculator tool of ArcGis 10.3: Normalized Difference Vegetation Index (NDVI), Tasseled Cap (which includes three sub-indices of brightness [TCB], greenness [TCG], wetness [TCW]), and a normalized disturbance index (DI) derived from Tasseled Cap sub-indices. These vegetation indices have been used to identify forest disturbances in temperate environments (Neigh *et al.*, 2014). For LANDSAT 8 OLI images, NDVI combines the red (R, band 4) and near-infrared (NIR, band 5) bands. NDVI is calculated as NDVI = NIR – R/NIR + R.

Tasselled Cap transformation optimizes vegetation analysis by using all non-thermal LANDSAT 8 OLI bands to produce TCB, TCG and TCW sub-indices named according to the features in the data that they emphasize. To estimate the values of TCB, TCG and TCW we used LANDSAT 8 OLI coefficients proposed by Baig *et al*. (2014), and calculated as (Kauth and Thomas, 1976; Crist, 1985): TCB = Σbi*OLIi, TCG = Σvi*OLIi, TCW = Σhi*OLIi. Where bi, vi and hi are the coefficients of the Tasseled Cap transformation for the calculation of the three values, and OLIi are the surface reflectance values for each non-thermal band (i) of the LANDSAT 8 image. DI (Disturbance Index) is obtained from the Tasselled Cap TCW and TCB sub-indices values and calculated as (Hais *et al.*, 2009): DI = TCW – TCB. We selected easily calculated vegetation indices that are accessible in most GIS and remote sensing software to facilitate its application by forest technicians on the Yucatan Peninsula (e.g., GRASS and QGIS, Ramdani et al., 2015; Zanchetta and Bitelli, 2017).

Field Sampling and Validation Data. Field sampling was conducted to obtain ground-based georeferenced data to validate and map forest disturbance in each 2014 ACA. Sampling was realized from May to September 2014 after logging activities were concluded in the ACAs. Within the large ACAs (Noh Bec and Felipe Carrillo Puerto) sampled areas consisted of two randomly selected 100 ha blocks (200 ha total), while in the small ACAs (Nuevo Guadalajara and Santa Maria Poniente) one 100 ha block was sampled. Within each 100-ha block, forest disturbance data was collected by georeferencing and mapping all felled tree stumps (felling gaps), skid trails, access roads (old and new) and log landings. It should be noted that the stumps of felled trees are found at distances generally no more than 20 m from skid trails. In addition, control points of undisturbed forest were also collected in randomly located unlogged areas within each ACA, located from 50 to 100 m away from the nearest skid trail or felling gap. Randomly selected points were obtained for each forest disturbance category in each sampled 100-ha block: 1) 100 for felling gaps or stumps; 2) 20 for skid trails at least 200 m apart; 3) 20 for logging roads, also 200 m apart; 4) 2 to 6 for log landings, depending on the ejido ACA; and 5) 20 control points in unlogged forest 50 to 100 m away from the nearest skid trail or felling gap.

Classification of Forest Disturbance from Selective Logging. To facilitate the use of remote sensing techniques by community forest enterprises and local forestry technicians we employ the automated un-supervised Iso Cluster or ISODATA classification using ArcMap 10.3. However, open-access remote sensing software mentioned above can also perform unsupervised or ISODATA classification of images. Binary maps were produced by classifying the images of the five calculated vegetation indices (NDVI, TCG, TCW, TCB and DI) as logged vs. unlogged areas (2 classes) for each 2014 ACA. Surface area and proportion of disturbed forest from selective logging was subsequently calculated (excluding masked pixels with cloud cover within two ACAs). In addition, ISODATA classifications of the five calculated indices were performed to derive maps of the five specific forest disturbance categories: 1) felling gap, 2) skid trail, 3) access road 4) log landing and 5) unlogged forest. Binary and specific disturbance classifications were then assessed based on field validation points.

Accuracy Assessment*.* We apply accuracy assessments to evaluate the effectiveness of vegetation indices calculated from LANDSAT 8 OLI images in detecting and mapping forest disturbance from selective logging. Accuracy assessments were performed for the binary forest disturbance classifications (logged and unlogged areas) and the specific logging disturbance type classifications (felling gaps, skid trails, access roads, log landings and unlogged). Validation points obtained from field sampling were employed for the accuracy assessments applying the method proposed by Olofsson *et al*. (2013) with the AccurAssess plugin for QGIS 3.4 (Mas et al 2014). This method produces and error-adjusted estimator and constructs confidence intervals for estimating classified areas, providing adjusted proportions of disturbed forest from selective logging based on the reference validation points.

RESULTS

Accuracy Assessments of Logged vs. Un-logged Areas. Figure 2 shows binary disturbance maps produced from each vegetation index (NDVI, TCW, TCB, TCG and DI) and for each ACA, categorized as logged and unlogged forest. The areas classified as logged show the combined impact of felling gaps, skid trails, logging roads and logging yards in each ACA. Accuracy assessment of the results indicated that detection of forest disturbance from selective logging using LANDSAT 8 OLI was possible, but not highly accurate (Table 2). Mean overall accuracies of selective logging disturbance classified from the calculated vegetation indices varied from 42% (DI in the ejido Santa Maria Poniente) to 72% (TCW in Nueva Guadalajara). Furthermore, 75% of the binary classifications (logged and unlogged forest) had mean overall accuracies greater than 60%, representing and overall good (40 to 70%), but not excellent accuracy (>70%), based on remote sensing standards used for accuracy assessments (Ismail and Jusoff, 2008).

Producer accuracies (omission errors) show how well a certain area can be classified, while user accuracies (commission errors) indicate how reliable the map can identify the class on the ground (Table 2). The best producer accuracies for classifying logged areas were found with indices TCG and TCW in Noh Bec and TCB and TCW in Santa María Poniente. The highest user accuracies for mapped logged areas were found with vegetation indices TCB and NDVI in Nueva Guadalajara and DI and NDVI in Felipe Carrillo Puerto. In general, producer accuracies for classifying unlogged areas were lower than those for logged areas, except for Nueva Guadalajara with very high producer accuracies for all vegetation indices. User accuracies to map unlogged areas were highest in Noh Bec and Santa Maria Poniente, with TCG and TCW indices respectively.

Forestry ejidos implementing RIL practices and with greater logging intensity (Noh Bec and Nueva Guadalajara) had higher overall accuracies. NDVI and TCG proved to be the best indices with respect to overall accuracy results, and these two same indices, followed by TCW, also seemed to predominate as the best indices according to producer and user accuracy results. NDVI, TCB, TCG and TCW vegetation indices showed potential in mapping and monitoring forest disturbance from selective logging on the Yucatan Peninsula. Felipe Carrillo Puerto, with the largest ACA and lowest harvest intensity had the greatest disturbance from selective logging in their ACA (Table 3). Furthermore, despite its low intensity logging, Felipe Carrillo Puerto had the greatest degree of disturbance per m^3 of timber harvested. Santa Maria Poniente, with the smallest ACA and moderate logging intensity, also showed high proportions of disturbance from logging, although calculated error adjusted proportions were lower compared to Felipe Carrillo Puerto. Likewise, the degree of disturbance per m^3 of timber extracted was much lower in Santa Maria Poniente, despite having a higher logging intensity than Felipe Carrillo Puerto.

In contrast, Noh Bec, with a large ACA and the highest logging intensity, had lower proportions of its ACA disturbed by logging, and the lowest calculated error adjusted proportions. In addition, Noh Bec, the FSC certified ejido implementing RIL practices, showed the lowest degree of disturbance per m^3 of timber extracted from its ACA. Nuevo Guadalajara, with a small ACA and moderate harvest intensity, had the lowest surface area and proportion of ACA impacted by selective logging. Nuevo Guadalajara, implementing IFM and RIL practices, such as the use of a modified agricultural tractor for skidding, also demonstrated a low scale of disturbance per m^3 of timber extracted.

Accuracy Assessments of Selective Logging Forest Disturbance Types. While access roads and log landings may be easily identified in the images with the naked eye, felling gaps and skid trails are harder to distinguish from each other (Figure 3). Accuracy assessments of specific forest disturbance types (Table 4) were obviously not as high as the binary logged vs. unlogged classifications, indicating the difficulty in separating specific logging activities. Disturbance from skidding and felling was the most difficult to differentiate. TCG showed the highest user accuracies for detecting log landings and felling gaps, as well as producer accuracies for log landing, access roads and unlogged forest classes. In contrast, producer accuracies for felling gaps and skid trails were much lower. Accuracy was mostly affected by classification errors between felling gaps and skid trails, which as noted above, are for the most part no more than 20 m apart, making differentiation between these disturbance types very difficult with LANDSAT 8 OLI images (30 m pixel).

DISCUSSION

This study showed accurate mapping of forest disturbance from selective logging using LANDSAT 8 derived vegetation indices. Nevertheless, there were limitations in discriminating the source of disturbance, such as felling, skidding and transporting timber. The overall accuracies of around 70% obtained for logged vs. unlogged forest maps were similar to those obtained for LANDSAT land use-land cover classifications in the region (Díaz-Gallegos *et al.*, 2001; Ellis and Porter-Bolland, 2008), demonstrating LANDSAT´s potential for mapping selective logging disturbance on the Yucatan Peninsula. Better overall accuracies in disturbance mapping were found in Nuevo Guadalajara and Noh Bec, both ejidos with higher timber harvest intensities. On the other hand, lower overall accuracies were obtained for the ejidos Santa María Poniente and Felipe Carrillo Puerto with much lower timber harvest intensities. While higher logging intensity apparently improves accuracy of mapping selectively logged areas, greater forest degradation from past forest use and natural impacts are suspected to cause lower accuracies in mapping unlogged areas. Felipe Carrillo Puerto, which in general show the lowest accuracies, is also the forestry ejido with a longer history of both natural and anthropogenic disturbances in its forest management area, being closer to the main urban and market center of the region (Felipe Carrillo Puerto). Noh Bec and Nueva Guadalajara, on the other hand, have a longer history and tradition of communal forest management and contain large areas with conserved forest cover, indicating that impacts from selective logging may be more difficult to detect and accuracies can become lower in more degraded forests compared to conserved forests.

LANDSAT images have also been demonstrated by Souza and Barreto (2000) to successfully map selective logging areas in the Brazilian Amazon using pixel-based soil fraction methods to detect log landings and impacted areas surrounding them, obtaining accuracies ranging from 69 to 80%. A much larger scale of logging operations in Brazil may explain higher accuracies compared to this study. Moreover, the remote sensing techniques applied are more complex for its application by local foresters or organizations working with forestry communities on the Yucatan Peninsula. In the Bolivian Amazon, Broadbent *et al.* (2006) also map disturbance from selective logging using NDVI derived from ASTER images (30 m resolution), and in Myanmar, Win *et al*. (2009) successfully detect selective logging also using NDVI from LANDSAT.

Furthermore, de Wasseige and Defourny (2004) detect selective logging impacts in tropical forests of the Central African Republic combining LANDSAT red, near infra-red (NIR) and mid-infrared (MIR) bands, although they caution that satellite acquisition geometry can affect this detection, performing best at or close to nadir. In this study, the best indices for mapping impacts from selective logging in ejidos were NDVI and TCG, which are strongly correlated (Samarawickrama *et al*., 2017), however, DI and TCW performed better in Nueva Guadalajara. These results confirm the relevance of detecting biomass changes to map disturbance since NDVI, which combines near-infrared and red band reflectance values, has been shown to effectively model above-ground biomass (Lopez-Serrano *et al*., 2016; Günlü *et al*., 2014; Zheng *et al*., 2004).

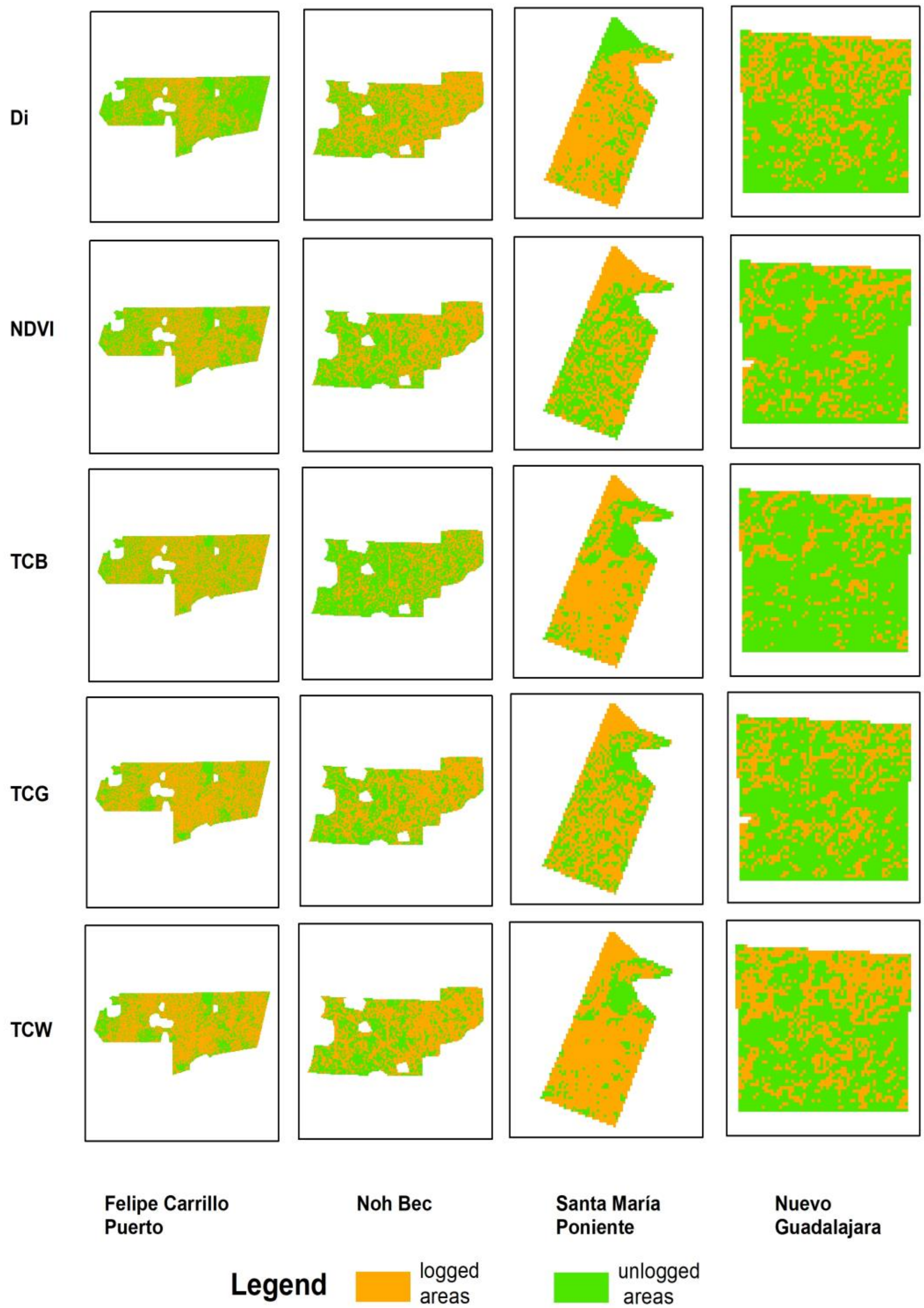

Figure 2. Binary classifications of logged and un-logged areas obtained from each vegetation index for the ACAs of the four sampled ejidos.

Table 2. Overall, producer and user accuracies (%) of selectively logged and unlogged areas (95% confidence intervals in parenthesis) obtained for disturbance maps classified from vegetation indices (NDVI, DI, TCB, TCG, TCW).

Ejido	Veg. Index	Overall Accuracy	Logged areas		Unlogged areas	
			Producer Accuracy	**User Accuracy**	**Producer Accuracy**	**User Accuracy**
Noh Bec	NDVI	66.9 (55.9-73.3)	70 (60-79.9)	59.3 (51.3-67.3)	64.5 (58.8-70)	74.5 (73-86)
	DI	59.7 (55.2-67.2)	75 (64.9-85)	53.8 (46.3-61.4)	47.2 (40-54)	69.6 (54-85.3)
	TCB	58.9 (51.5-66.3)	44.4 (37-51.9)	57.5 (48.4-66.6)	71.5 (55.9-77)	59.7 (49.9-70)
	TCG	67.7 (60.9-74.4)	77.4 (67.5-87.2)	58.8 (51-66.6)	60.6 (54.9-66.4)	78.7 (67-90.4)
	TCW	64.8 (58.1-71.5)	75.8 (67.5-84)	59 (60.9-73.2)	55.6 (49.3-61.8)	73.2 (61.6-84.8)
Felipe Carrillo Puerto	NDVI	63.4 (58.6-68.2)	61.9 (58.2-65)	82.3 (76.4-88.3)	67.2 (58.8-75.7)	41.6 (33.9-49.4)
	DI	58.6 (53.8-63.5)	50.8 (47.3-54.3)	84.2 (78.3-90)	77.3 (70-84.6)	40.7 (32.5-47)
	TCB	55.7 (50.7-60.8)	61.6 (58.2-65)	71.7 (64.9-78.5)	41.5 (33.2-49.8)	31.1 (23.5-38.5)
	TCG	70.7 (66-75.4)	77.4 (74.1-80.7)	81 (75.5-86.4)	53.6 (45-62.1)	48.2 (39-57.4)
	TCW	62.1 (57.1-67.1	70.1 (66.9-73.2)	75.4 (69-81.8)	42.1 (33.7-50)	35.7 (27.7-43.6)
Santa María Poniente	NDVI	66.3 (59.6-73)	68.5 (62.4-74.6)	68.6 (58.7-78.4)	63.7 (55.8-71.6)	63.7 (54.8-72.5)
	DI	42.2 (35.2-49.2)	64.1 (57.7-70)	46.3 (46.3-53.9)	18.1 (10.5-25.7)	31.4 (16-46.8)
	TCB	60.5 (53.8-67.3)	84.7 (78.3-91.2)	56.4 (48.6-64.1)	37.5 (31.4-43.5)	72 (58.6-85.4)
	TCG	62.8 (56.1-69.5)	73.8 (67.1-80.4)	60.6 (51.9-69.3)	51.7 (44.9-58.5)	66.2 (55.6-76.7)
	TCW	62 (55.5-68.6)	91.5 (86.2-96.7)	57 (49.4-64.6)	33.8 (28.4-39)	80.5 (67.6-94.3)
Nuevo Guadalajara	NDVI	67.5 (61.6-73.3)	42.4 (37.7-47)	96.6 (90.2-100)	98.2 (94.8-100)	58.2 (50.8-65.6)
	DI	68.7 (62.4-75)	50.7 (44.4-57)	80.3 (70.3-90.3)	87.2 (81.4-93)	63.3 (55.2-71.3)
	TCB	67 (60.9-73)	38 (33.4-42.5)	96.9 (91-100)	98.6 (96.2-100)	59.8 (51.8-66.7)
	TCG	68.5 (62.2-74.7)	48.5 (42.6-54.4)	84.3 (74.3-94.2)	90 (84.4-95.9)	61.7 (53.9-69.5)
	TCW	72.1 (66-78.2)	61.8 (55.5-68.2)	80.2 (71-89.5)	83.3 (76.6-90)	66.6 (58.5-74.8)

Table. 3. Total area (ha), percentage of disturbance from selective logging (%) and area disturbed per cubic meter of timber extracted in ACAs (ha m^{-3}).

Ejido	NDVI		TCG		TCW	
	ha (%) [%]*	ha m^{-3a}	ha (%) [%]*	ha m^{-3a}	ha (%) [%]*	ha m^{-3}
Felipe Carrillo Puerto	887 (53.5) [66.4-76]	0.5	1139.2 (68.7) [67.1-76.6]	0.7	1105.1 (66.6) [66.7-76.7]	0.7
Noh Bec	390.7 (50.1) [35.4-49.5]	0.1	431 (55.2) [35.2-48.9]	0.1	458.2 (58.7) [39-52.5]	0.1
Santa María Poniente	96.6 (53.7) [46.9-60.3]	0.1	110.1 (61.6) [43.5-56.9]	0.2	141 (78.5) [42.4-55.6]	0.2
Nuevo Guadalajara	63.9 (24.09) [49.2-60.9]	0.1	79.3 (29.8) [45.8-58.3]	0.2	107 (40.2) [46.1-58.4]	0.2

*Error adjusted proportion of disturbance from selective logging based on Olofsson accuracy assessment with reference points.

Table 4. Accuracy assessment results for classifications of forest disturbance types in ACAs of each ejido.

		OA	ULL	UFG	UST	ULR	UF	PLL	PFG	PST	PLR	PF
Noh Bec	NDVI	23	100	95.9	0.5	21.3	20.5	100	7.4	2	100	100
	DI	28.6	100	96.8	1	18.5	19.6	100	15.2	1.9	100	97.9
	TCB	22.2	25	96.1	2.4	7.3	23.3	25.7	17	52.8	37.7	44.8
	TCG	43.5	100	94.1	1.1	12.7	27.9	100	31.9	1.9	100	95.2
	TCW	3.6	0.3	100	2.2	8.9	17.2	73.7	2.1	35.5	42	1.9
Felipe Carrillo Puerto	NDVI	32.1	2.3	74.4	3	0	44.2	17.2	4.6	13.4	0	86.3
	DI	31.2	8.1	61.5	16.7	7.4	48.6	74.3	6.3	8.9	80.8	72.7
	TCB	20.3	2.9	66.7	12.9	3.8	28.7	62.3	2.3	24.7	9.1	57.4
	TCG	29.2	1.2	69.3	12	6.5	10.5	14.7	40.2	13.5	60.3	3.6
	TCW	17.8	1.6	56.1	3	4.1	27.6	52.4	11.9	3.9	13.5	26.9
Santa María Poniente	NDVI	30.8	16.7	0	100	33.3	41.9	45.1	0	0.9	16.3	88.9
	DI	42.8	40	0	66.7	12.5	40.3	25.7	0	24.9	4.7	78.5
	TCB	29.7	4.3	0	48.5	9.1	41.7	15.3	0	21.6	6.7	47.1
	TCG	29.9	23.1	0	47.1	4.3	45.9	38.9	0	12.1	6.9	63.3
	TCW	30.3	11.1	0	39.6	4	44	13.1	0	15.3	7.6	57.7
Guadalajara	NDVI	31.3	7.7	100	6.5	4	46.1	100	3.7	15.7	29.7	98
	DI	11.5	1.4	95.2	2.3	5.9	20.9	100	4.5	29	14.6	27
	TCB	39	0.6	88.4	12.5	6.8	54.7	55.4	24.9	19.2	9.8	78.5
	TCG	42.3	1.3	84.9	8.7	100	49.5	100	22.3	19.9	5.8	95
	TCW	36.9	0.6	87.4	8.7	10.5	55.5	56.6	16.9	16	16.9	85.8

OA.- Overall Accuracy; **ULL**.- User Accuracy Log Landing; **UFG**.- User Accuracy Felling Gaps; **UST**.- User Accuracy Skid Trail; **ULR**.- User Accuracy Logging Road; **UF**.- User Accuracy Forest; **PLL**.- Producer Accuracy Log Landing; **PFG**.- Producer Accuracy Felling Gaps; **PST**.- Producer Accuracy Skid Trail; **PLR**.- Producer Accuracy Logging Road; **PF**.- Producer Accuracy Forest.

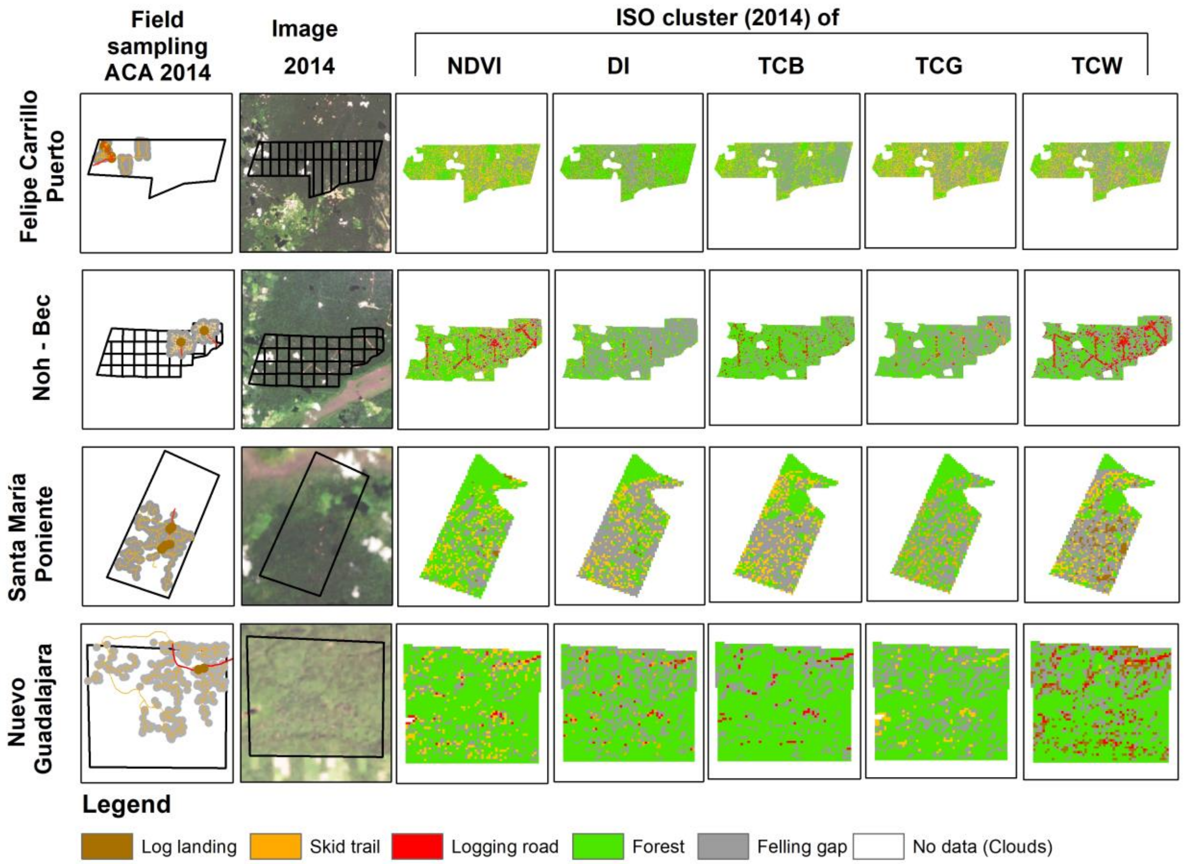

Figure 3. Classification of forest disturbance categories from selective logging (e.g. log landing, skid trail, logging road, felling gap and un-logged forest) obtained from each vegetation index for the ACAs of the four sampled ejidos.

Similar studies in temperate evergreen forests demonstrated that DI and TCW were better indicators of forest disturbance from logging (Neigh et al., 2014; Hais et al., 2009; Jin and Sader, 2005). In these cases, vegetation moisture plays a greater role in discriminating disturbance considering that both indices include "wetness". Nueva Guadalajara, being furthest south of all sampled ejidos, is also located in an area with greater precipitation and moisture, indicating that DI and TCW may perform better in wetter conditions.

Timing in detecting and mapping disturbance from selective logging is also crucial since vegetation recovery can occur quickly, sometimes becoming undistinguishable from unlogged forests in medium resolution satellite images as soon as 3 to 6 months after harvesting in Bolivia (Broadbent *et al*. 2006) or 1 to 2 years in the Brazilian Amazon (Souza and Barreto 2000). Thus, many authors recommend that images should be evaluated no later than 1 year after harvesting to successfully detect disturbance from logging (Stone and Lefebvre, 1998; de Wasseige and Defourny, 2004). In our study region, this may have to be much sooner (<1 year) considering the high resiliency of forests on the Yucatan Peninsula (Turner, 1978) as well as lower timber harvest intensities compared to other tropical forest regions.

Mapped disturbance from selective logging in ACAs also indicate differences in the application of IFM and RIL practices. Noh Bec, a FSC certified ejido, implements both IFM and RIL (e.g. direct felling, skid trail and harvest planning), but also has a large ACA and high logging intensity, but impacted a small proportion of its ACA (around 50%) and had a low harvest impact (0.1 ha·m^3). In comparison, Felipe Carrillo Puerto, without RIL practices, with the largest ACA, and the lowest harvest intensity, impacted a greater proportion of their ACA (around 70%) and had the highest harvest impact (0.7 ha·m^3), notwithstanding its very low logging intensity. These results possibly point to differences in disturbance impacts between ejidos implementing IFM and those that don´t. A similar result was found for the ejidos with smaller ACAs, Nuevo Guadalajara and Santa María Poniente. A much lower proportion of mapped disturbance (around 30%) was observed for Nuevo Guadalajara which implements RIL practices, compared to Santa Maria (around 60%) that doesn´t, despite both having similar harvest volumes and logging intensities. In great part, this may be explained by the use of a modified agricultural tractor for timber extraction (skidding) in Nueva Guadalajara instead of a conventional skidder which is larger and heavier, causing greater forest disturbance.

This study exemplifies the potential to detect and map selective logging disturbances in ejidos on the Yucatan Peninsula using LANDSAT 8 OLI images, which can also be applied to assess and monitor forest degradation. Monitoring degradation has been especially crucial to pursuing REDD+ goals, and specifically to implement their monitoring, reporting and verification (MRV) system (Angelsen *et al*., 2009) in collaborating countries such as Mexico. However, degradation has certainly proven to be a much greater challenge to monitor than deforestation, considering that forest cover is still maintained, and changes in forest cover may be very subtle (Herold and Skutsch, 2011). Consequently, MRV of degradation processes was distinguished as a separate necessity by REDD+, in addition to MRV of deforestation, and specifically associated to monitoring within forest activities, such as logging, firewood collection and others (Morales-Barquero *et al*. 2014; Herold and Skutsch, 2011). A combination of both remote sensing and field-based methods, as applied in this study, has been recommended as the most cost-effective means to achieve this (Goetz *et al*., 2015). In addition, IFM and RIL have been recently promoted to reduce forest impacts and carbon emissions from selective logging in the tropics and thus reduce potential degradation in managed forests (Angelsen *et al*., 2009; Griscom *et al*., 2009). On the Yucatan Peninsula, RIL practices can reduce carbon emissions from selective logging by almost half a ton per m^3 of timber extracted (Ellis *et al*. 2019). This research also demonstrated by mapping disturbance that ejidos that implemented RIL practices can reduce up to 40% of the forest damaged by selective logging, for example by using a modified agricultural tractor to extract timber. Forest managers, technicians or NGOs can easily implement the methods described in this study (i.e. combining remote sensing and field-based validation points) to assess improvements in reducing impacts and carbon emissions from implementing RIL and IFM in their ejido.

However, the application of LANDSAT 8 OLI images to discriminate forest disturbance from specific selective logging practices (e.g. felling, skidding and transporting timber) was not possible. In the Brazilian Amazon, the ability to identify forest impacts from log landings greater than 900 m2 and areas impacted by roads, skid trails and tree felling in a 350 m radius was possible; however, they also failed to differentiate impacts from specific harvest activities (Monteiro and Souza, 2003). In the Bolivian Amazon, Broadbent *et al.* (2006) finds that impacts from felling gaps must be greater than 400 m^2 to be distinguished from unlogged forest using ASTER images (30 m resolution). This is similar to what is feasible using LANDSAT imagery despite better spatial and spectral resolution. Arevalo *et al*., (2016) also claim that impacts from specific selective logging operations can be very difficult to distinguish using LANDSAT images, particularly when harvest intensities are low. Lower intensity logging practices in temperate forest are also more difficult to identify; in British Columbia, Canada, for example, producer accuracies obtained from TCG of LANDSAT images showed clear cuts and residual cuts were much easier to map (83 and 79% respectively) in contrast to partial cuts (63%) where harvesting intensity is much lower (Jarron et al. 2017).

As would be expected, due to greater removal of the forest canopy in log landings and logging roads, they were the specific disturbances most accurately mapped. In some cases, producer accuracies for log landings and logging roads were above 90% such as in Noh Bec where new log landings and roads were established within the ACA. Low producer and user accuracies for logging roads were obtained in ejidos where older logging roads were re-used, and which tend to have more canopy coverage, as was the case in Nuevo Guadalajara. Distinguishing specific disturbances caused from felling and skidding proved to be the most difficult using LANDSAT 8 OLI images, and producer and user accuracies for skid trails were generally low in all ejidos. The lower harvest intensities on the Yucatan Peninsula may explain these poor results, for example felling gaps in the region may vary in size from 100 to 300 m^2, which is smaller than the minimum of 400 m^2 claimed to be needed to detect felling impacts using ASTER 30 m resolution imagery in the Amazon (Broadbent *et al*., 2006). While skidding logs do create impacts on understory vegetation and smaller diameter trees (< 20 cm dbh), sufficient canopy cover of remaining larger trees may make detection and mapping of skid trails difficult. Also, the fact that felled trees are mostly no more than 20 m from the nearest skid trail in our study area, makes it difficult to distinguish between felling and skidding impacts. Furthermore, as mentioned above, the use of a modified agricultural tractor in the case of Nuevo Guadalajara may also affect the detection of skid trails, having the lowest producer and user accuracies for mapping skid trails.

For these reasons, the use of LANDSAT 8 OLI images to map and monitor impact reductions from specific harvest or RIL practices (e.g. directional felling, use of a winch with a long cable and skid trail planning) is not recommended without the compliment of ground mapping, higher resolution imagery and/or LIDAR data. For example, Read (2003) clearly demonstrates that IKONOS high resolution images (4 m) were much more successful in detecting skid trails and felling gaps than LANDSAT, which were successful in detecting only major logging features in selectively logged forest of Brazil. Asner *et al*. (2010) use airborne LIDAR to successfully differentiate selective logging impacts from timber harvesting in the Peruvian Amazon, and Ellis *et al*. (2016) also show how airborne LIDAR data could accurately map (98%) selective logging impacts in East Indonesia. Impacts within harvested cutting blocks amounted to 69% in the Indonesian selectively logged tropical forests, similar to the proportion impacted in Felipe Carrillo Puerto, but higher than the other ejidos of this study. Despite the high precision obtained in mapping impacts from selective logging in Indonesia using LIDAR data, impacts from disturbance caused by skid trails were also difficult to distinguish, with only a 59% agreement. Our study also demonstrated poor user and producer accuracies in distinguishing selective logging impacts from skid trails. However, combining all disturbance types raises the accuracy of mapping forest disturbance from selective logging and can provide accurate mapping of the overall forest impacts from harvesting operations.

CONCLUSION

Our study showed that up to 70% accuracy was obtained using LANDSAT 8 OLI to detect and map forest disturbance impacts from selective logging on the Yucatan Peninsula. However, field sampling and validation is necessary to guide and evaluate the mapping process. Mapping disturbances from specific harvesting practices was much less reliable with very low accuracies (< 43%), requiring high resolution imagery or LIDAR data to improve accuracy. This study also showed that the ejidos applying IFM and RIL can potentially reduce disturbance from selective logging in their ACAs by up to 50%, while also increasing harvest volumes. Forest impacted per m^3 of timber extracted can be reduced from 0.7 to 0.1 ha by applying RIL practices, particularly using a modified agricultural tractor instead of a skidder to extract timber. The methodology presented can be easily performed by local foresters and forestry ejidos using open-access GIS and remote sensing software to monitor potential degradation and assess impact reductions by applying IFM and RIL practices.

Acknowledgments
The authors are grateful to El Colegio de la Frontera Sur (ECOSUR) in Chetumal, Quintana Roo for their valuable support in carrying out the present investigation. We acknowledge the support of the Consejo de Ciencia y Tecnología (CONACYT) to IUHG via the graduate student scholarship.

Funding. Funding for this research was made possible by the United States Agency for International Development (USAID), under the terms of the Cooperation Agreement No. AID-523-A-11-00001 (Proyecto de Reducción de

Emisiones por la Deforestación y la Degradación de Bosques de México) implemented by the main awardee The Nature Conservancy (TNC) and its partners (Rainforest Alliance, Woods Hole Research Center and Espacios Naturales y Desarrollo Sustentable).

Conflict of interest. The authors confirm that there are no known conflicts of interest associated with this publication.

Data availability. Data are available with IUHG (urielxal@gmail.com) upon reasonable request**.**

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