TROPICAL DRY FOREST DEGRADATION ESTIMATION AT LOCAL SCALE WITH UAV IMAGES

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KEYWORDS: Forest disturbance, forest attributes

ABSTRACT: Forest degradation is a dynamic process, and its accurate mapping and detection has been limited by the lack of spatial and temporal resolution of conventional remote sensing, especially in tropical dry forests (TDF). The objective of this work is to assess UAV images for mapping and quantifying forest degradation of the TDF at local scale. Firstly, the accuracy of UAV images to estimate forest attributes (canopy height, canopy cover, biomass and frequency of individuals) is evaluated. These attributes are then integrated to estimate the status of forest degradation. UAV images were obtained for both rainy and dry season, also field measurements at 22 plots. UAV images were processed by photogrammetry of motion structure, and a canopy height model (CHM) and a mosaic in RGB are created. The CHM calculates canopy height, in combination with the RGB mosaic, the canopy cover was delimitated through an object-based image analysis. For the estimation of biomass and frequency of individuals, multiple linear regression models are developed, which allows the attributes data from field to be related to the height and canopy coverage estimated by UAV images. Forest degradation states are estimated using a relative degradation index. The preliminary results show that the processing of the UAV images has obtained a good accuracy for the average and maximum canopy height with an error of 0.4 - 3.1 m, respectively. The delimitation of the canopy cover has an overall accuracy of 95%. Forest attributes from UAV images are expected to continue to be calculated reliably, compared to those at the ground level.

1. INTRODUCTION

Forest degradation is defined as the loss of some particular attribute, function or service due to disturbances to its composition, structure, function of ecosystems, interaction between species or the physical environment (Ghazoul et al. 2015). Forest degradation contributes to biodiversity loss, acceleration of climate change, and loss of a multitude of benefits, which affects negatively the livelihoods of marginalized populations that depend directly on forests (Barlow et al., 2007; Houghton et al., 2012; Angelsen and Wunder 2003). Particularly, the tropical dry forest (TDF) is important for carbon supply, and it represents one of the ecosystems with great diversity and endemism worldwide, nevertheless it is one of the most threatened and yet less studied ecosystems (Sánchez-Azofeifa et al. 2005).

Recently there has been a particular interest in assessing forest degradation (Olander et al., 2008; DeFries et al., 2007). However, this is difficult because it is a continuous process and implies transformations (degradation / regeneration) in the forests that remain as forests. Putz and Redford (2010) and Goetz et al., (2014) recommended to estimate degradation at different levels through the establishment of thresholds. Forest degradation implies transformations in the forest structure that can only be detected at a local scale and that conventional remote sensing has not been able to estimate it accurately due to the lack of spatial and temporal resolutions (Herold et al., 2011). Data with much higher spatial and temporal resolutions are needed to map the subtle differences in the change of forest structures and this need is even greater in TDF, because its phenology varies seasonally (Mertz et al., 2012; Sánchez-Azofeifa et al., 2005; Gibbs et al., 2007). UAV images represent a data source with detailed and frequent low-cost observations at local scales (Paneque-Gálvez et al., 2014; Zahawi et al., 2015), which makes them potentially useful to estimate forest degradation in TDF, and benefit the calculation of forest degradation at regional and even national scales.

The UAV images offer high-resolution ortho-mosaics, 3D point cloud and digital surface models through photogrammetry and motion structure processes. Its main utility has been focused on the estimation of structural characteristics of 3D vegetation (Dandois and Ellis 2010). Some forest attributes such as canopy height, canopy cover, and biomass estimation have already been estimated from UAV images (Dandois and Ellis 2013, Ota et al., 2015, Torres-Sánchez et al., 2015). However, it is necessary to continue to estimate these forest attributes for different forest types in different disturbance and phenological conditions.

Given the potential of UAV images in extraction of key forest attribute variables, and the difficulties in mapping forest degradation in the TDF, this study hypothesizes that UAV images contribute significantly to improve the mapping and estimation of forest degradation. This study focuses on assessing the potential of UAV images to map and quantify forest degradation of TDF at the local scale. The objectives are: (1) to assess the usefulness of UAV images in estimating forest attributes in the TDF at the local level; and (2) to map and quantify forest degradation through the integration of forest attributes through an Index of relative degradation. For this, a case study is carried out in the Sierra Gorda Biosphere Reserve of Guanajuato, one of the most biodiverse and protected natural areas of the country (CONANP 2013).

2. METHODOLOGY

Figure 1 is a flowchart showing the methodology of this work, including the acquisition of UAV images and data from in-situ; data processing to estimate and validate forest attributes and the integration of data attributes to determine forest degradation at local scale.

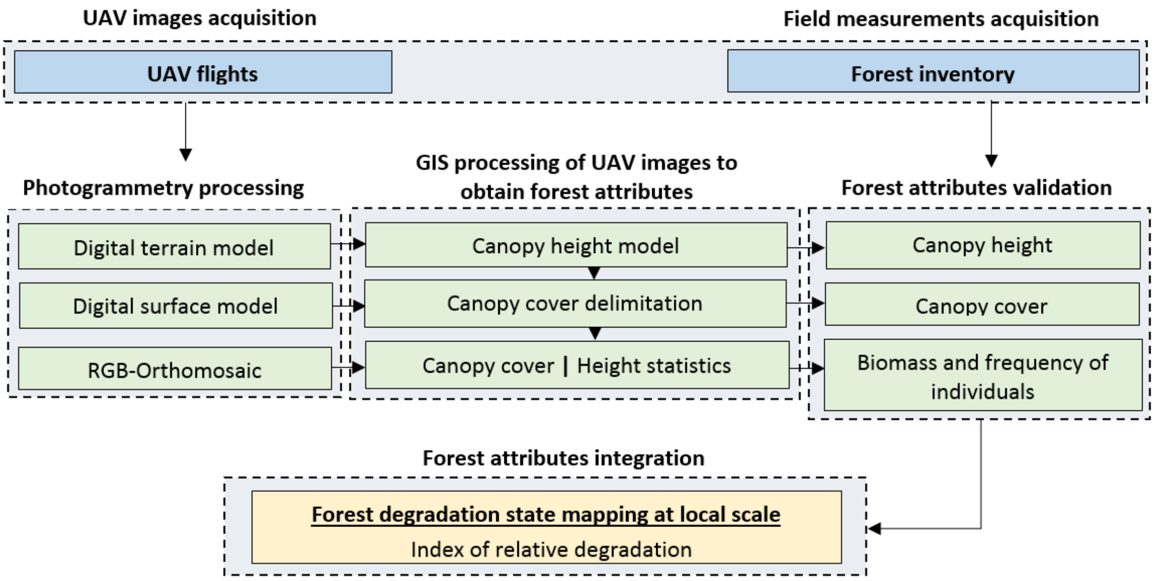

Figure 1. Methodological flowchart. The methodology includes three main steps. The first step, in blue color, is the acquisition of the data in this analysis. Consequently, the boxes in green color, constitutes the particular processing of the data. Finally, the third step is the integration of the processing data to obtain the main result of the analysis.

2.1 Study area

The study area is located in the central part of the Sierra Gorda Biosphere Reserve of Guanajuato, municipality of Victoria, Guanajuato, Mexico (Figure 2). This area is home to a high diversity of TDF species. In addition, it is the habitat of species of felines distinguished in the reserve, among which is *Puma yagouaroundi, Lynx rufus* and *Puma concolor* (Charre-Medellín et al., 2012). The main cause of degradation in this area is cattle grazing and ranching. This area was chosen because it is relatively homogeneous in terms of natural ecosystems and land use.

Figure 2. The study area. The upper two maps indicating the location of the biosphere reserve in Mexico. The lower map is a zoom of the biosphere reserve, where the red box comprises the study area. The map includes geographic features details of the study area.

2.2 Field work: Forest inventory and UAV images acquisition

UAV flights and forest inventory for 22 sites were carried out, which were defined based on an equation that calculates a total number of samples, considering a confidence interval of 80% and a margin of error of 10% (Burt and Barber, 1996). The distribution of these sites was defined by stratified random sampling, according to 3 categories of percentage of tree covers (10-40%, 40-70% and 70-100%) (Rocha 2015) in order to obtain greater heterogeneity in the degradation levels of the selected sites (Figure 3).

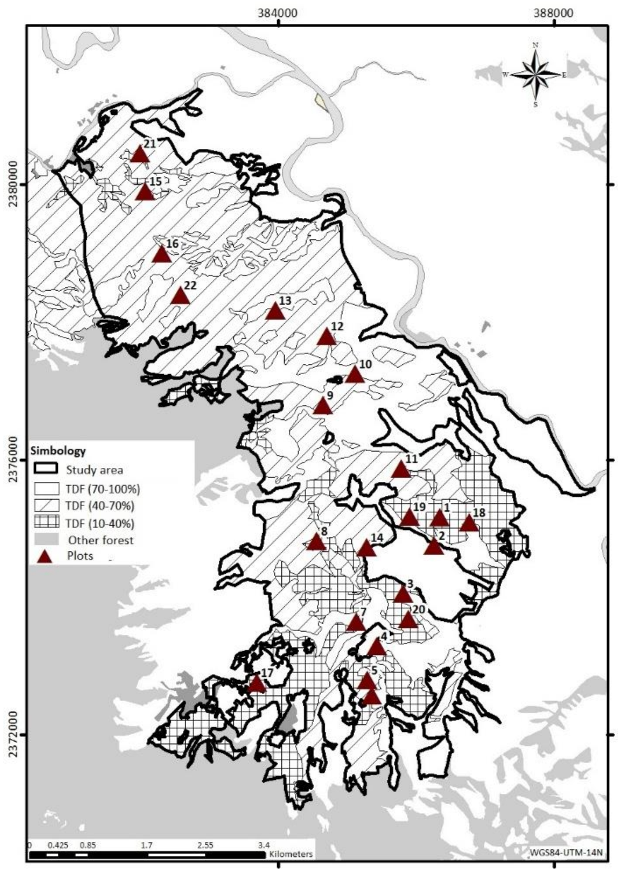

Figure 3. Distribution of the study plots. The map shows the limit of tropical dry forest (TDF) and the location of the plots through the different categories of tree cover taken into account in this work.

For each plot, UAV images were obtained by flights at 100 meters' height for both rainy and dry seasons, covering areas from 1 to 8 hectares. For each of the sites surveyed, 4 ground control points distributed around each plot were collected to improve the spatial reference of the images. Forest attributes data were obtained through inventory at circular plots of 400 m² each for variables including tree height, diameter at breast height (DBH, 1.3m) > 7.5 cm, common species name and percentage of tree cover. Forest inventory data were used to calibrate and validate forest attributes obtained from UAV images.

2.3 Processing of UAV Images

UAV images were processed by using Agisoft PhotoScan Professional software version 1.2.6 to generate 3D spatial data such as dense point clouds, digital surface models and ortho-mosaics.

2.4 Estimation of canopy height

The canopy height estimation is based on a canopy height model (CHM), generated through the subtraction of digital terrain model (DTM) from digital surface model (DSM). The DSM for each site is obtained from the processing of UAV images for the rainy season. The DTMs in open cover canopy plots are generated from the extraction of terrain points for rainy season cloud points. The DTMs for closed cover canopy plots are generated based on the processing of UAV images for the dry season because the lack of leafs allow the detection of point cloud at ground level due to the SfM algorithms are not able to detect the surface of canopy cover (Dandois and Ellis 2013). The reliability of the CHM is determined from the comparison of statistics of the estimated field canopy heights against statistical heights obtained by CHM through a linear regression model. Statistics obtained from CHM include maximum, minimum, mean, median and deciles.

2.5 Canopy cover classification

Areas of canopy cover was obtained by an object-based classification of UAV images. The images were first segmented using a stable mean-shift algorithm available in the Orfeo software (Michel et al. 2015). Mean-shift is an algorithm of grouping pixels of an image in regions of the same characteristics, in this case the tones of RGB mosaic. This technique does not require preliminary knowledge of the number and shape of regions and has presented consistent results in high resolution images (Comaniciu and Meer 2002, Michel et al. 2015). Subsequently, for each segment, the mean value of CHM is extracted, a threshold classifier based on this data is applied, where segments with a mean canopy height greater than 3 meters are classified as canopy cover. The resultant canopy cover is compared to the canopy cover by photointerpretation. The comparison is carried out by means of a confusion matrix and the overall accuracy of the canopy cover classification was evaluated.

2.6 Estimation of biomass and frequency of individuals

Biomass and the frequency of individuals for the 24 plots were calculated from the field measurements. The biomass was calculated by an allometric equation established for TDF (Martinez-Yrizar et al. 1992). A multiple linear regression model is performed to estimate the biomass and frequency of individuals at each site. This model considers the biomass and frequency of individuals, calculated from the field data, as dependent variables by explanatory variables of CHM (maximum, minimum, mean, median and deciles) and the percentage of canopy cover for each plot. The equation regression model is used to estimate beyond the plots these variables based on the best explanatory variables.

2.7 Forest degradation estimation

To estimate the degradation of TDF, a normalized index of relative degradation (NIRD) was applied (Jardel-Peláez et al., 2013). This index integrates forest attributes calculated from UAV images and field data (canopy height, canopy cover, biomass and frequency of individuals) and then to classify them into different states of forest degradation.

The first step of the index consists of the normalization of the considered variables (equation 1).

$$V_e = \frac{x - \bar{x}}{SD} \qquad (1)$$

Where V_e is the normalized variable, x is the value of the variable for each of the sites, X is the mean of the variable for all study sites and SD is the standard deviation of all study sites. An average of these normalized variables is then calculated by equation 2.

$$NIRD = \frac{Ae + Be + Ce + De}{n} \qquad (2)$$

Where NIRD is the normalized index of relative degradation, *Ae, Be, Ce* and *De* correspond to each of the normalized variables and n is the number of variables. The state of forest degradation is estimated according to the classified values of the degradation indices (Table 1).

Table 1. Classification of the INDR (Jardel-Peláez et al. 2013). The index comprises four categories determinate from its resultant value. The categories with more positives values correspond to the less degraded. Four finally categories of forest degradation are estimated.

INDR	Value	Degradation level
1	> 1	Low level Degradation
2	1 - 0	Moderate Degradation
3	0 - (-1)	High level Degradation
4	< (-1)	Very high level Degradation

3. PRELIMINARY RESULTS

Based on the processing results of UAV images, only for 3 and 4 study plots, the mean and maximum canopy height within the plots have so far been accurately determined, with recorded errors ranging from 0.4 to 3.1 m, respectively (Figure 4).

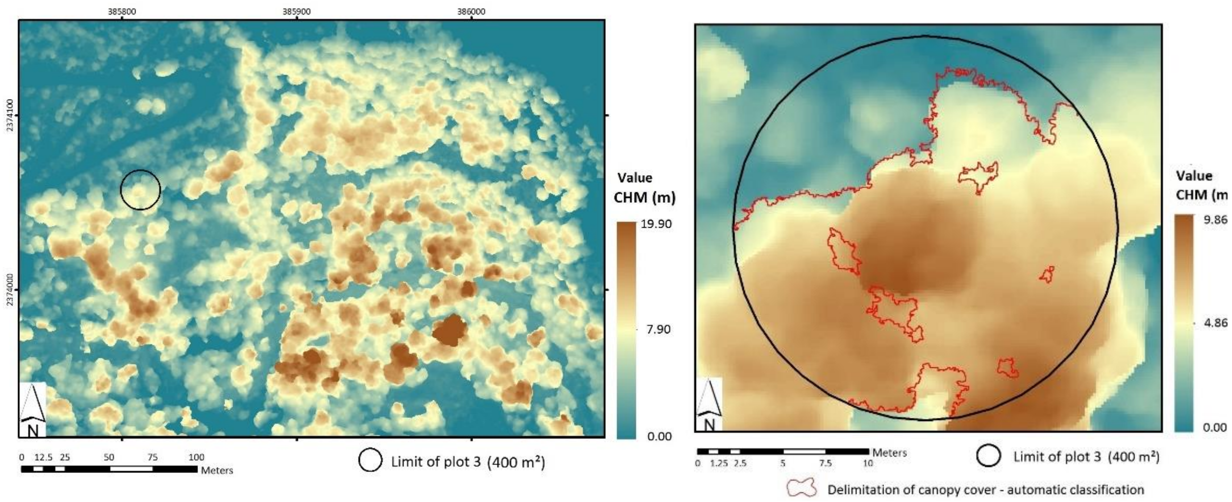

Figure 4. Canopy height model (CHM). The left image shows the distribution of canopy height at window level. The right image represents the canopy height within the plot 3 and the limit of canopy cover taken into account to obtain statistics of canopy height at plot level.

The delimitation of canopy cover has been estimated with an overall accuracy of 95% and with errors of omission and commission of 1 and 12% respectively (Figure 5).

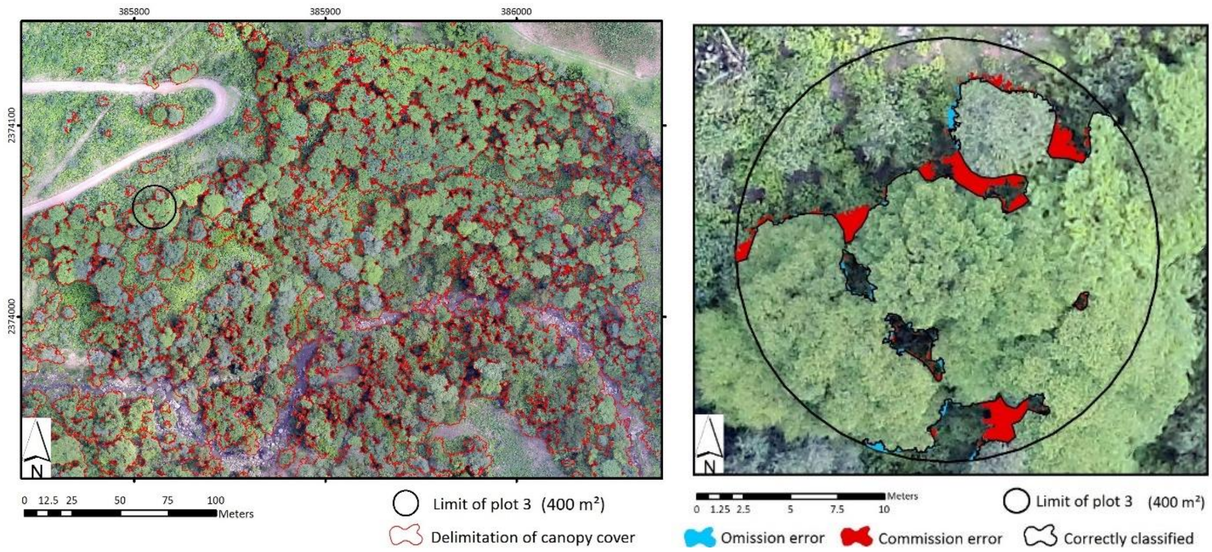

Figure 5. Delimitation of canopy cover. The left image represents the RGB orthomosaic of forest and its delimitation of canopy cover at window level. The right image shows the validation parameters for the delimitation of canopy cover at plot level.

From the field data, the degradation index has been calculated, where the categories with the greatest degradation have a lower forest structure, it is expected that the estimation of the forest attributes is reliable, compared to those estimated at the ground level.

ACKNOWLEDGEMENT

Fieldwork and UAV images for this work were financed with resources from project PAPIIT IA 104117, "*Mapeo de la degradacion forestal utilizando imagenes de serie de tiempo de indice de vegetacion del sensor MODIS".*

REFERENCES

Angelsen, A., and S. Wunder. 2003. "Exploring the Forest-Poverty Link: Key Concepts, Issues and Research Implications." Economist, no. 40: 68. doi:10.17528/cifor/001211.

Barlow, J., T. A. Gardner, I. S. Araujo, T. C. Avila-Pires, A. B. Bonaldo, J. E. Costa, M. C. Esposito, et al. 2007. "Quantifying the Biodiversity Value of Tropical Primary, Secondary, and Plantation Forests." Proceedings of the National Academy of Sciences 104 (47): 18555–60. doi:10.1073/pnas.0703333104.

Charre-Medellín, J., V. Sánchez-Cordero, G. Magaña-Cota, M. Álvarez-Jara & F. Botello. 2012. "Jaguarundi (Puma yagouaroundi) in Guanajuato, Mexico". The Southwestern Naturalist, 57(1), 117-118.

CONANP 2013. Comisión Nacional de Áreas Naturales. Borrador del Programa de Manejo de la Reserva de la Biósfera Sierra Gorda de Guanajuato. México, D.F.

Portillo-Quintero, C., A. Sanchez-Azofeifa, J. Calvo-Alvarado, M. Quesada, and M. M. do Espirito Santo. 2015. "The Role of Tropical Dry Forests for Biodiversity, Carbon and Water Conservation in the Neotropics: Lessons Learned and Opportunities for Its Sustainable Management." Regional Environmental Change 15 (6). Springer Berlin Heidelberg: 1039–49. doi:10.1007/s10113-014-0689-6.

Dandois, Jonathan P., and C. E. Erle. 2010. "Remote Sensing of Vegetation Structure Using Computer Vision". Remote Sensing 2 (4): 1157–76. doi:10.3390/rs2041157.

Dandois, Jonathan P., and C. E. Erle. 2013. "High Spatial Resolution Three-Dimensional Mapping of Vegetation Spectral Dynamics Using Computer Vision". Remote Sensing of Environment 136. The Authors: 259–76. doi:10.1016/j.rse.2013.04.005.

DeFries, R., A. Frédéric, B. Sandra, H. Martin, D. Murdiyarso, B. Schlamadinger, and C. de Souza. 2007. "Earth Observations for Estimating Greenhouse Gas Emissions from Deforestation in Developing Countries". Environmental Science and Policy 10 (4): 385–94. doi:10.1016/j.envsci.2007.01.010.

Ghazoul, Jaboury, Z. Burivalova, J. Garcia-Ulloa, and L. A. King. 2015. "Conceptualizing Forest Degradation." Trends in Ecology and Evolution 30 (10). Elsevier Ltd: 622–32. doi:10.1016/j.tree.2015.08.001.

Gibbs, H. K., B. Sandra, J. O. Niles, and J. A. Foley. 2007. "Monitoring and Estimating Tropical Forest Carbon Stocks: Making REDD a Reality." Environmental Research Letters 2 (4): 45023. doi:10.1088/1748-9326/2/4/045023.

Goetz, Scott J, Matthew Hansen, Richard A Houghton, Wayne Walker, Nadine Laporte, Jonah Busch, Matthew Hansen, Nadine Laporte, and Jonah Busch. 2014. "Measurement and Monitoring for REDD+: The Needs, Current Technological Capabilities, and Future Potential." Climate and Forest Paper Series, no. December 2014: 49.

Martin, H., R. Román-Cuesta, D. Mollicone, Y. Hirata, P. Van Laake, G. P. Asner, C. Souza, M. Skutsch, V. Avitabile, and K. MacDicken. 2011. "Options for Monitoring and Estimating Historical Carbon Emissions from Forest Degradation in the Context of REDD+." Carbon Balance and Management 6 (1). BioMed Central Ltd: 13. doi:10.1186/1750-0680-6-13.

Houghton, R. A., J. I. House, J. Pongratz, G. R. Van Der Werf, R. S. Defries, M. C. Hansen, C. Le Quéré, and N. Ramankutty. 2012. "Carbon Emissions from Land Use and Land-Cover Change." Biogeosciences 9 (12): 5125–42. doi:10.5194/bg-9-5125-2012.

Jardel-Peláez-Peláez, E.J.; Morfín-Ríos, J.; Ghilardi, A.; Martínez-Bravo, R.; Padilla-Velarde, E.; Ramírez-Michel, U.; Rodríguez, J.; Flores-Nieves, J.; Rodríguez-Vázquez, G.; Aguilar-Pérez, V. Evaluación del Estado de Conservación de la Selva Baja Caducifolia de la Cuenca Media del Río Ayuquila; Universidad de Guadalajara: Autlan, Jalisco, 2013.

Koh, Lian Pin, and Jaboury Ghazoul. 2010. "A Matrix-Calibrated Species-Area Model for Predicting Biodiversity Losses due to Land-Use Change." Conservation Biology 24 (4): 994–1001. doi:10.1111/j.1523-1739.2010.01464.x.

Martinez-Yrizar, A, J Sarukhán, A Perez-Jimenez, E Rincón, M Maass, A Solis-Magallanes, and L Cervantes. 1992. “Above-Ground Living Phytomass of a Tropical Deciduous Forest in the Coast of Jalisco, México.” Journal Tropical Ecology 8: 87–96.

Mertz, Ole, Daniel Müller, Thomas Sikor, Cornelia Hett, Andreas Heinimann, Jean-Christophe Castella, Guillaume Lestrelin, et al. 2012. “The Forgotten D: Challenges of Addressing Forest Degradation in Complex Mosaic Landscapes under REDD+.” Geografisk Tidsskrift-Danish Journal of Geography 112 (January 2015): 63–76. doi:10.1080/00167223.2012.709678.

Michel, Julien, David Youssefi, and Manuel Grizonnet. 2015. “Stable Mean-Shift Algorithm and Its Application to the Segmentation of Arbitrarily Large Remote Sensing Images.” IEEE Transactions on Geoscience and Remote Sensing 53 (2): 952–64. doi:10.1109/TGRS.2014.2330857.

Olander, Lydia P, Holly K Gibbs, Marc Steininger, Jennifer J Swenson, and Brian C Murray. 2008. “Reference Scenarios for Deforestation and Forest Degradation in Support of REDD: A Review of Data and Methods.” Environmental Research Letters 3 (2): 25011. doi:10.1088/1748-9326/3/2/025011.

Ota, Tetsuji, Miyuki Ogawa, Katsuto Shimizu, Tsuyoshi Kajisa, Nobuya Mizoue, Shigejiro Yoshida, Gen Takao, et al. 2015. “Aboveground Biomass Estimation Using Structure from Motion Approach with Aerial Photographs in a Seasonal Tropical Forest.” Forests 6 (11): 3882–98. doi:10.3390/f6113882.

Paneque-Gálvez, Jaime, Michael K. McCall, Brian M. Napoletano, Serge A. Wich, and Lian Pin Koh. 2014. “Small Drones for Community-Based Forest Monitoring: An Assessment of Their Feasibility and Potential in Tropical Areas.” Forests 5 (6): 1481–1507. doi:10.3390/f5061481.

Putz, Francis E., and Kent H. Redford. 2010. “The Importance of Defining ‘Forest’: Tropical Forest Degradation, Deforestation, Long-Term Phase Shifts, and Further Transitions.” Biotropica 42 (1): 10–20. doi:10.1111/j.1744-7429.2009.00567.x.

Rocha, F. (2015). Degradación forestal en la Reserva de la Biosfera Sierra Gorda de Guanajuato (Tesis de Licenciatura). Universidad de Guanajuato: México.

Sánchez-Azofeifa, G. Arturo, Mauricio Quesada, Jon Paul Rodríguez, Jafet M. Nassar, Kathryn E. Stoner, Alicia Castillo, Theresa Garvin, et al. 2005. “Research Priorities for Neotropical Dry Forests.” Biotropica 37 (4): 477–85. doi:10.1111/j.1744-7429.2005.00066.x.

Torres-Sánchez, Jorge, Francisca López-Granados, Nicolás Serrano, Octavio Arquero, and José M Peña. 2015. “High-Throughput 3-D Monitoring of Agricultural-Tree Plantations with Unmanned Aerial Vehicle (UAV) Technology.” PloS One 10 (6): e0130479. doi:10.1371/journal.pone.0130479.

Zahawi, Rakan A., Jonathan P. Dandois, Karen D. Holl, Dana Nadwodny, J. Leighton Reid, and Erle C. Ellis. 2015. “Using Lightweight Unmanned Aerial Vehicles to Monitor Tropical Forest Recovery.” Biological Conservation 186. Elsevier Ltd: 287–95. doi:10.1016/j.biocon.2015.03.031.