

Proceeding Paper

Monitoring Forest Dynamics in the Palmira Area of Ecuador Using the LandTrendr and Continuous Change Detection Algorithms [†]

Marco Castelo ^{1,*}, Jorge López ¹, Edgar Merino ¹, Gustavo Buñay ¹, Mayra Peñafiel ¹, Rene Villa ¹, Johanna Santana ³, Edwin Tipán ⁴

¹ INSTITUTO SUPERIOR TECNOLÓGICO BOLIVAR; georgehola@gmail.com (J.L.), ef_merino@yahoo.es (E.M.), ivancanta10@hotmail.com (G.B.), penafiel.mayrae@gmail.com (M.P.), memo_re7@yahoo.es (R.V.)

² INSTITUTO SUPERIOR TECNOLÓGICO EDUPRAXIS; cdydsantana@gmail.com

³ INSTITUTO SUPERIOR TECNOLÓGICO RIOBAMBA; tippedwin@gmail.com

* Correspondence: javiercastelo2072@gmail.com

[†] Presented at the 5th International Electronic Conference on Remote Sensing, 7–21 November 2023; Available online: <https://ecrs2023.sciforum.net/>

Abstract: Deforestation is a significant global concern, with forests vital for climate balance, water conservation, and rainfall. In Palmira, Chimborazo, Ecuador, a pattern of afforestation followed by deforestation has been observed, influenced by both public and private activities. Some areas, due to prolonged erosion, have even turned into deserts. This study utilized the Google Earth Engine platform and algorithms like LandTrendr and CCDC to analyze satellite imagery from 2000 to 2020, aiming to understand the forest dynamics in four specific Palmira locations. The results were consistent with documented patterns of afforestation and deforestation in the region. For instance, the Galte Laime area experienced an increase in forest cover until 2006, after which significant deforestation occurred. In contrast, Palmira Dávalos, often referred to as the Palmira Desert, consistently showed minimal vegetation, a result of centuries of erosion. Galte Cuatro Esquinas presented a decline in forest cover until 2009, after which regrowth was observed. Jatun Loma initially maintained its forest cover but eventually experienced deforestation, followed by a reforestation phase. In conclusion, this research offers a comprehensive insight into Palmira's forest dynamics using advanced algorithms and satellite-based time series. The findings emphasize the importance of remote sensing tools in monitoring forest changes, which can be pivotal for informed decision-making in forest management and conservation in the region.

Keywords: forest dynamics; deforestation; landtrendr algorithm; satellite imagery; remote sensing analysis

Citation: To be added by editorial staff during production.

Academic Editor: Firstname Last-name

Published: date



Copyright: © 2023 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Forests are essential in global ecology, storing carbon, preventing droughts, and promoting rainfall, protecting water resources and soil [1–5].

Between 1990 and 2000, Ecuador lost approximately 198,000 hectares of natural forests annually, making it one of the Latin American countries with the highest deforestation rates [6]. From 2000 to 2008, Ecuador's forested area decreased to 59%. However, between 2008 and 2018, there has been a significant recovery. Most deforested areas were converted into agricultural lands, with a smaller percentage used for infrastructure due to agricultural expansion and extensive shifts in land use [7].

In Palmira, Chimborazo province, there is a constant cycle of afforestation and deforestation due to agricultural expansion. Even though projects like PROFAFOR and the GAD of Guamote reforest the area, over time, these same entities deforest for economic

gain. Species such as pines and eucalyptus have been planted, with community efforts involving various local entities and associations [8].

The study aims to identify disruptions in the altered forests of Palmira, whether caused by humans or natural factors. The objective is to model the 20-year forest dynamics. Reference points include Jatun Loma, Galte Laime, Galte Cuatro Esquinas, and Palmira Dávalos in the "Palmira Desert."

The aim of this research is to use the GEE platform and the LandTrendr and CCDC algorithms with Landsat images to describe the forest dynamics caused by deforestation, reforestation, and natural processes in the Palmira area, Chimborazo province, in Ecuador.

2. Materials and Methods

2.1. Study Area

The Palmira parish is located in Ecuador, specifically in Chimborazo, in the Guamote canton, at an altitude of 3,280 meters above sea level. Temperatures range from 12-13°C and it has approximately 16,000 inhabitants, predominantly indigenous. Both Kichwa and Spanish languages are spoken. The primary economic activity is agriculture, with main crops being white onion, corn, and peas. This can be observed in Figure 1.

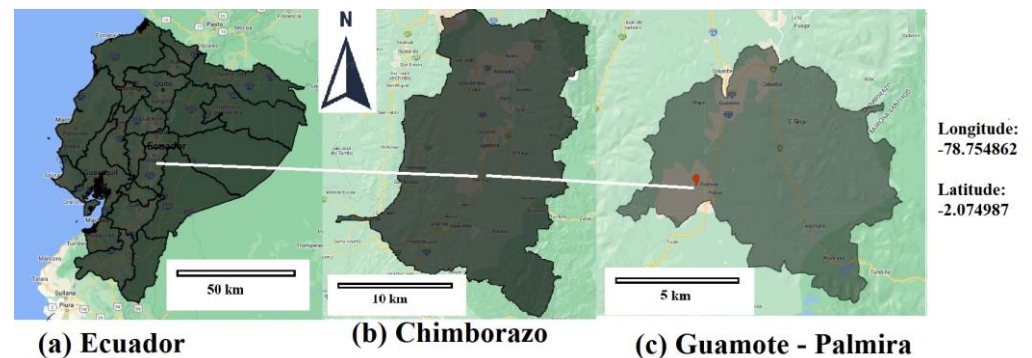


Figure 1. Location of Palmira in the Guamote canton - Ecuador.

2.2. Data

Landsat images of the Palmira parish were obtained through the GEE platform, spanning the years 2000 to 2020. Images from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operation Land Imager (OLI) were used, creating a median dataset. These data have undergone atmospheric correction and include a mask for clouds, shadow, water, and snow produced with [9].

Due to the differences in reflective wavelength between the TM/ETM+ and OLI sensors, the bands from Landsat 8 OLI were harmonized to the TM/ETM+ equivalents using the regression equations mentioned in by [10].

2.3. Methodology

LandTrendr are spatiotemporal algorithms detecting changes via satellite image time series, primarily from Landsat. It extracts spectral change trajectories on Earth's surface [11]. Applied in areas like: forest restoration [12], pest-induced tree mortality [13], forest cover trends, ancient settlement ID, abandoned land mapping, and biomass change assessment [14].

Evaluation and construction use NDVI. LandTrendr's spatial-temporal dynamics for a pixel are depicted in illustration 2. This illustrates main algorithm elements: event magnitude, duration, disturbances, stability, over 20 years.

After obtaining the dataset as described in the previous section, we proceed to adjust the LandTrendr parameters, which are detailed in Table 1, along with the values used in this study.

Table 1. Description of LandTrendr algorithm parameters. Adapted from [15].

Parameters	Value	Meaning
maxSegments:	6	This represents the maximum number of segments allowed for the given pixel's temporal series to be fitted, as outlined in the technical section of the paper.
spikeThreshold:	0.8	The spike threshold parameter controls the extent of filtering, with a value of 1.0 corresponding to no filtering, and lower values corresponding to more aggressive filtering, as explained in the technical section of the paper.
vertexCountOvershoot:	3	This sets the maximum number of candidate vertex years.
preventOneYearRecovery	True	Prevent the recovery of one year.
recoveryThreshold	0.25	To prevent unrealistic recovery following a disturbance, a value of 1.0 signifies that the constraint is disabled, while a value of 0.25 would mean that segments recovering completely faster than four years ($4 = 1 / 0.25$) are not allowed.
pvalThreshold:	0.05	P-value threshold, finding good models using these criteria based on the p-value parameter.
bestModelProportion:	0.75	Best model proportion. Thus, an adjustment can be made that will allow choosing a model with more segments as long as it falls within a defined proportion of the best-scoring model. This proportion is set by the best model proportion parameter. For example, a value of 0.75 for the best model proportion would allow selecting a more complex model if its score exceeded 75% of the best model's score.
minObservationsNeeded	6	Minimum required observations.

Parameter	Description.
Raster.	The input multidimensional raster layer.
Bands for temporal masking.	The band IDs of the green band and the SWIR band to be used for cloud, cloud shadow, and snow masking. If no band IDs are provided, no masking will occur. The band ID values should be integers separated by spaces.
Chi-square threshold for change detection.	The chi-square change probability threshold. If an observation's calculated change probability exceeds this threshold, it is flagged as an anomaly, indicating a potential change event. The default value is 0.99.
Minimum consecutive anomaly observations.	The minimum number of consecutive anomaly observations that must occur before an event is considered a change. A pixel must be flagged as an anomaly for the specified number of consecutive time periods to be considered a real change. The default value is 6.
Update adjustment frequency (in years).	The frequency at which the time series model should be updated with new observations. The default option is to update the model once per year.

2.4. CCDC Algorithm

The CCDC algorithm is used for detecting land cover changes through satellite image series, initially developed in MatLab, then ported to Python, and recently integrated into Google Earth Engine [16]. It utilizes Landsat data to detect fluctuations in spectral bands or indices like NDVI, EVI, NBR. Changes can be seasonal or abrupt, such as deforestation and natural disasters. Functioning as a linear time series, it updates with new observations and employs a harmonic regression model to identify changes in pixel values. Breakpoints indicate shifts in spectral-temporal behavior due to coverage changes. Implemented in GEE, it is user-friendly and delivers good results using the default parameters, as shown in Table 2.

Table 2. Description of algorithm parameters CCDC.

3. Results

As previously mentioned, four reference points will be utilized, which are depicted in Figure 2. The exact coordinates for these locations are detailed in Table 3. The LandTrendr and CCDC algorithms detect disturbances, revealing their timing, magnitude, and duration. Disturbances primarily result from ongoing reforestation and deforestation by companies and residents, in collaboration with the Government of Guamote.

Table 3. Geographical coordinates of the Palmira area - Ecuador.

	Galte, Laime	Palmira Dávalos	Galte, Cuatro Esquinas	Jatun Loma
Latitude	-2.0749	-2.06384	-2.038821	-2.07128
Longitude	-78.7806	-78.7545	-78.783493	-78.81612

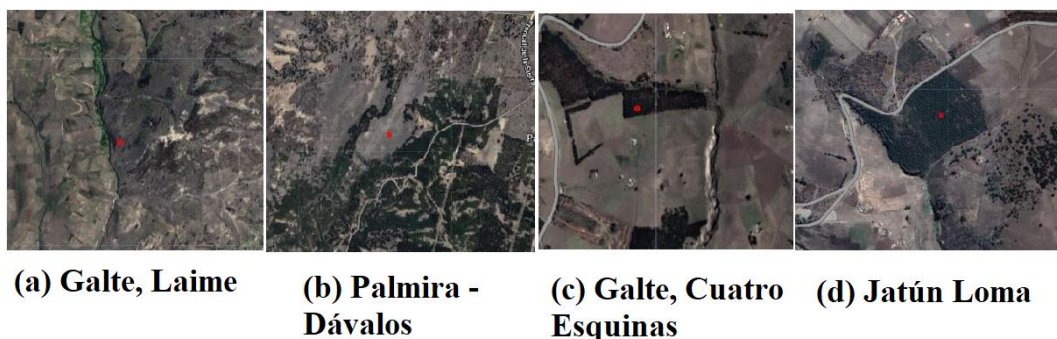


Figure 2. Satellite images of the Geographical Coordinates of Palmira - Ecuador.

As observed in Figure 3(a) and Figure 4(a), both LandTrendr and CCDC exhibit similar patterns in the Galte Laime sector. A growth in the forested area is noticeable up to around the year 2006, after which it remains relatively stable until 2012 for LandTrendr and 2014 for CCDC. Subsequently, significant changes indicate a substantial deforestation event that continues to the present day.

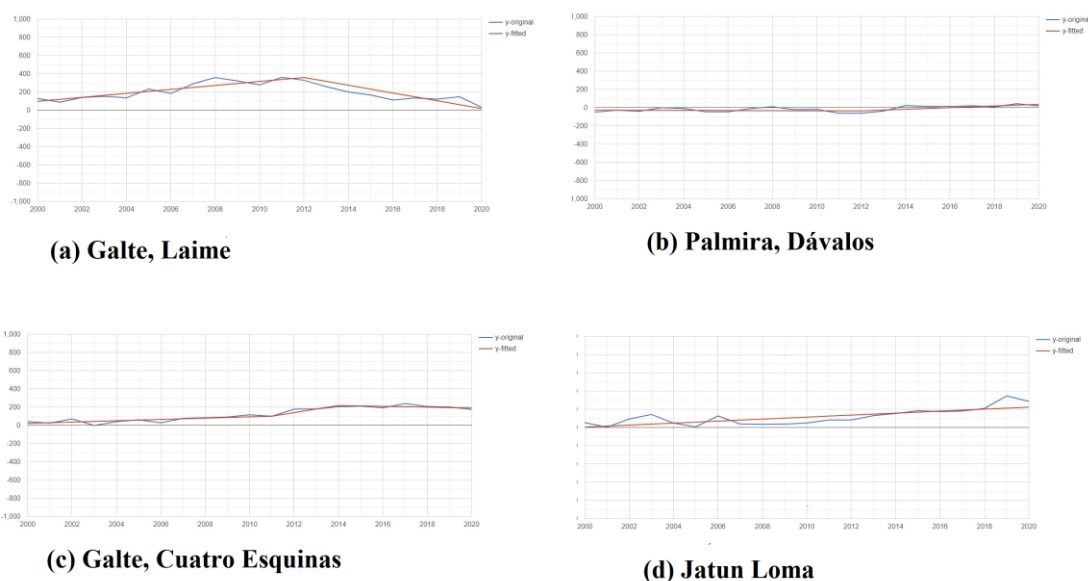


Figure 3. Disturbance trends with the LandTrendr algorithm.

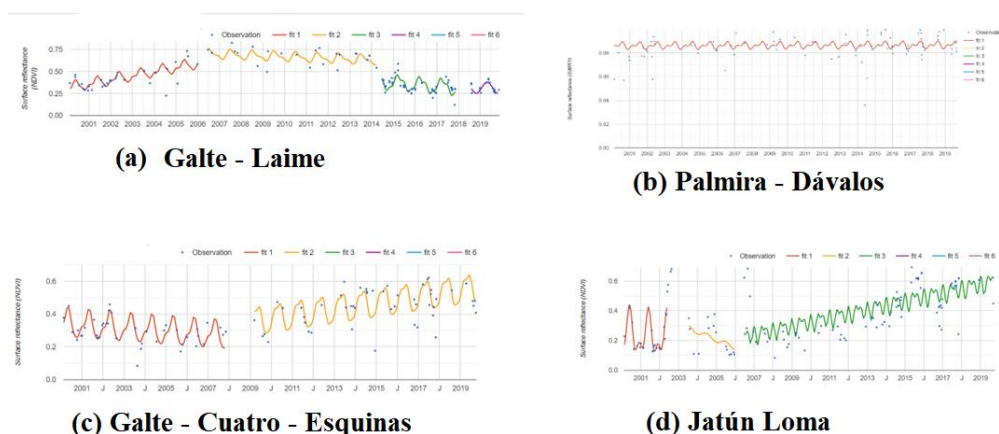


Figure 4. Disturbance trends with the CCDC algorithm.

In both the LandTrendr and CCDC algorithms, there is a consistency observed over the years since there is no vegetation in this location, and it has remained a desert due to erosion caused over decades. Currently, it is a tourist site where people are drawn to its uniqueness. This location is commonly referred to as the 'Palmira Desert', as can be seen in Figure 3(b) and 4(b).

In Figures 3(a) and 3(c), a consistent downward trend is observed in the Cuatro Esquinas sector until around the year 2009, followed by an upward trend, indicating that the forested area has begun its regeneration up to the present day. We speculate that this area has not been significantly impacted by human activity, as there are no abrupt changes evident in the figures generated for both LandTrendr and CCDC.

In the Jatun Loma sector, as can be seen in Figures 3(c) and 3(d), a distinctive pattern is evident. Up until the year 2002, stability is observed, as both the CCDC harmonics and the LandTrendr trend remain constant with a periodic tendency. Subsequently, a steady curve with a negative inclination indicates deforestation without abrupt changes, possibly due to climatic conditions or some type of pest impact. Later, a positive slope is discerned, suggesting gradual reforestation. Meanwhile, the LandTrendr algorithm shows a continuous forest growth from the year 2000 to the present day.

4. Conclusions

From 2000 to 2020, the spatiotemporal coverage in the Palmira parish was evaluated, specifically in areas such as Jatun Loma and Galte Laime. Using the LandTrendr and CCDC algorithms, a significant forest dynamic was detected, with changes ranging from extreme deforestation to gradual growth due to climatic factors and pests.

Documents from Bravo [8,17], indicate reforestation agreements in Ecuador, including Palmira. These allow the company to extract trees for commercial purposes. These efforts began in 1993 with species like pine and eucalyptus. From 1999, native species were integrated. However, 90% of the plantations are pines. Notably, many of these trees are burned by farmers to expand arable lands. Additionally, since 2005 there has been a push for the planting of exotic species for commercial purposes. For instance, in the Galte sector, 850 hectares were planted between 2000 and 2010.

Since 2010, deforestation has been continuous, culminating in 2015 when the Galte Jatun Loma community sold 200 hectares in accordance with the PROFAFOR contracts.

The LandTrendr and CCDC algorithms have proven to be highly effective in detecting forest alterations. While some data align with previous records, others differ due to the vastness of the studied area and the lack of specific records of activities like controlled fires. However, in general, these algorithms have provided a clear insight into the phenology of Palmira over the last two decades.

Author Contributions: .

Funding:

Institutional Review Board Statement: .

Informed Consent Statement: .

Data Availability Statement: .

Acknowledgments:

Conflicts of Interest:

References

1. Houghton, R.A.; Byers, B.; Nassikas, A.A. A role for tropical forests in stabilizing atmospheric CO₂. *Nature Clim. Change* 2015, 5, 1022–1023.
2. Sheil, D.; Murdiyarso, D. How forests attract rain: An examination of a new hypothesis. *BioScience* 2009, 59, 341–347.
3. Miura, S.; et al. Protective functions and ecosystem services of global forests in the past quarter-century. *Forest Ecol. Manag.* 2015, 352, 35–46.
4. Braatz, S.; Fortuna, S.; Broadhead, J.; Leslie, R. Coastal protection in the aftermath of the Indian Ocean tsunami: What role for forests and trees? FAO, 2007. Available online: <https://www.fao.org/3/ag127e/ag127e.pdf> (accessed on 18 January 2022).
5. Cohen, W.B.; Healey, S.P.; Yang, Z.; Zhu, Z.; Gorelick, N. Diversity of algorithm and spectral band inputs improves landsat monitoring of forest disturbance. *Remote Sens.* 2020, 12, 1673. doi:10.3390/rs12101673.
6. MAE. Programa Nacional de Reforestación con fines de Conservación Ambiental, Protección de Cuencas Hidrográficas y Beneficios Alternos; Ministerio del Ambiente, 2020. Disponible en: <https://www.ambiente.gob.ec/wp-content/uploads/downloads/2020/04/REFORESTACION.pdf> (Accessed on January 18, 2022.).
7. Sierra, R.; Calva, O.; Guevara, A. PROAMAZONÍA; Quito: 2021. Disponible en: <https://www.proamazonia.org/wp-content/uploads/2021/06/Deforestacio%CC%81n Ecuador com2.pdf>.
8. Bravo, A. Sistematización de la experiencia de la protección ambiental a través de la siembra de árboles en las comunidades rurales de la parroquia de Palmira, cantón Guamote. MSc Thesis, UPS, Quito, 2012.
9. Zhu, Z.; Woodcock, C. E. Object-based cloud and cloud shadow detection in landsat imagery. *Remote Sens. Environ.* 2012, 118, 83–94.
10. Roy, D. P.; Kovalskyy, V.; Zhang, H. K.; Vermote, E. F.; Yan, L.; Kumar, S. S.; Egorov, A. Characterization of landsat-7 to landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sens. Environ.* 2016, 185, 57–70.
11. Kennedy, R. E.; Yang, Z.; Cohen, W. B. Detecting trends in Forest Disturbance and recovery using yearly Landsat Time Series: 1. Landtrendr — temporal segmentation algorithms. *Remote Sens. Environ.* 2010, 114(12), 2897–2910.
12. Griffiths, P.; Kuemmerle, T.; Kennedy, R. E.; Abrudan, I. V.; Knorn, J.; Hostert, P. Using annual time-series of landsat images to assess the effects of forest restitution in post-socialist Romania. *Remote Sens. Environ.* 2012, 118, 199–214.

13. Meigs, G. W.; Kennedy, R. E.; Cohen, W. B. A landsat time series approach to characterize bark beetle and defoliator impacts on tree mortality and surface fuels in conifer forests. *Remote Sens. Environ.* 2011, 115(12), 3707–3718.
14. Main-Knorn, M.; Cohen, W. B.; Kennedy, R. E.; Grodzki, W.; Pflugmacher, D.; Griffiths, P.; Hostert, P. Monitoring coniferous forest biomass change using a landsat trajectory-based approach. *Remote Sens. Environ.* 2013, 139, 277–290.
15. Kennedy, R. Landtrendr. openMRV. 2011. Available online: http://www.openmrv.org/en/web/guest/-/modules/mrv/modules_2/landtrendr (accessed el 18 de marzo de 2022).
16. Arévalo, P.; Bullock, E.L.; Woodcock, C.E.; Olofsson, P. A suite of tools for continuous land change monitoring in Google Earth engine. *Front. Clim.* 2020, 2. Available online: <https://doi.org/10.3389/fclim.2020.576740> (December 15, 2022).
17. PROFAFOR. Beneficios e impactos socioeconómicos del programa de. 2015. Available online: https://nanopdf.com/download/beneficios-e-impactos-socioeconomicos-del-programa-de_pdf (accessed on January 3, 2023).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.