Understanding Land Use Conflicts With Landsat Time Series

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Abstract

Time series analysis of remote sensing data is an efficient method for observing, monitoring, and characterizing land use/cover change (LUCC). However, it is challenging to integrate local knowledge into these estimations to improve the explanation of land use conflicts (LUCs) in terms of LUCC. LUCs are the irrational utilization of land systems (LS) caused by individual stakeholders pursuing their own interests and competing for land resources. The purpose of this study is to understand the relationship between LUCs and LUCC. San Miguel el Grande (SMG), Oaxaca, Mexico, is a case study from 1993 to 2023. The method was two principal phases: 1) Landsat time series analysis and point analysis with the CCDC algorithm (Continuous Change Detection and Classification); and 2) process tracing to explain the causal relationship. The results indicate a classification accuracy of around 88% per year. The breakpoints in the harmonic regression can detect LUCC related to the LUCs reported by the news and local people. These findings provide information about the impact of social drivers on forest lands. They help formulate public policies that consider the local context in rural municipalities with valuable timber resources.

1. Introduction

Land use/cover change (LUCC) is the emergent result of a myriad of interactions and feedbacks between various actors, technologies, institutions, cultural practices, and the associated demands and motivations for land use, which collectively constitute land systems (LS) (Meyfroidt, 2016). LS is a complex and open system generated by the transformation, utilization, and adaptation of the land surface and its upper and lower spaces of the Earth, including the biophysical environment, land use, and social economy, all of which are mutually generated, restricted, and indivisible (Li et al., 2020).

The objective of Land System Science (LSS) is to comprehensively understand the intricate interactions between human and natural systems on various scales (Lambin and Meyfroidt, 2011). LSS integrates multiple disciplines, including geography, ecology, sociology, economics, and remote sensing (Zhao et al., 2024), with strong links to remote sensing and geographical information sciences, as well as various modeling approaches (Turner et al., 2021). So, understanding of LS strongly depends on the availability of accurate land change data (Li et al., 2020).

LSS considers interconnected and multifaceted processes such as population growth, urbanization, agricultural expansion, industrialization, infrastructure development, and natural resource exploitation that lead to CCUS a form of human influence on the environment (Zhao et al., 2024; Zhou et al., 2020). CCUS can lead to Land use conflicts (LUCs), which are considered drastic shock events. LUCs are defined as the irrational use of LS caused by conflicting stakeholders who pursue their own interests and compete for land resources, resulting in the fragmentation and complexity of LS and hindering the optimal utilization of the general benefits of LS (Qin et al., 2024).

In general, there are four conceptual approaches to study LUCs: 1) focus on social conflicts between actors, 2) spatial focus on spatial conflict between land uses, 3) normative focus on the discrepancy between actual and more environmentally sustainable land use, because in reality and norms are incompatible, and 4) political focus on competing political or planning goals, competing laws or competing norms regarding land uses (Fienitz, 2023). In this study, we consider the spatial approach.

The relationship between LUCs and LUCC has been studied on different analysis scales: from a global study of the impact of armed conflict on forest loss in international border areas (Zheng et al., 2023) to local studies exploring this relationship, such as the Pixquiac River subbasin, Veracruz, Mexico (Chablé-Rodríguez et al., 2022). Remote sensing (RS) is the primary methodological approach to spatially explaining this relationship (Baumann and Kuemmerle, 2016), utilizing data from the Landsat satellite, which has been freely available and open since 1972 (Wulder et al., 2022; Zhu et al., 2019). This enables the conduct of time series analyses (Aung, 2021; Gorsevski et al., 2012).

In Mexico, the average annual net forest loss was 221,000 hectares between 1990 and 2000, 143,000 hectares per year during the 2000-2010 period, and net deforestation averaged 125,000 hectares per year from 2010 to 2020 (CONAFOR, 2022). Approximately 39% of forests and 60% of tropical forests are located within indigenous territories(CONAFOR, 2023). Of Mexico´s 26 million rural inhabitants, 17.7 million live in forest land, where 15,584 are communal groups that live on rural lands that are most often held in common and managed with some level of government control called ejidos (Thoms and Betters, 1998), and communities with more than 200 forest hectares are located (Chapela and Merino, 2019).

Until April 2020, more than 500 agrarian conflicts had affected 352 agricultural centres. Oaxaca is the state with 32.2% of indigenous farm centers. Approximately 283 agrarian conflicts (56%) occurred in the Mixtec region (Registro Agrario Nacional, 2021), where scientific studies have documented community forest enterprises(Hernández-Aguilar et al., 2017) and forest

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transitions (Lorenzen et al., 2020). Recently, San Miguel el Grande (SMG) has been a conflict zone, with reported casualties resulting from territorial conflicts (Matías, 2024), and high-value maderable resources in an ecoturistic area known as Santuario de las Aves (Meganoticias, 2023).

Nonetheless, few studies have addressed the relation between LUC and LUCC. Thus, to address this gap in the literature, the objective of this study is to understand the causal relationship between LUCs and LUCC, using Landsat time series in SMG, Oaxaca, Mexico, from 1993 to 2023.

2. Materials and methods

2.1 Study area

SMG is a municipality with an area of 103.607 km2 located in $17°02'45''$ N, $97°37'10''$ W at an elevation of 2,479 m above sea level in Oaxaca, Mexico. Until 2020, there were 4,313 *Ñuu Savi* Mixtec indigenous people, and seven out of ten were poor (CONEVAL, 2020). LUCs are considered the leading cause of fires and illegal logging, which have degraded the forest at a rate of 20 to 50 hectares per year (H. Ayuntamiento Constitucional de San Miguel El Grande, Tlaxiaco, Oaxaca, 2023).

Figure 1 shows location of SMG in the global, national (A), Oaxaca (B), and study area (C).

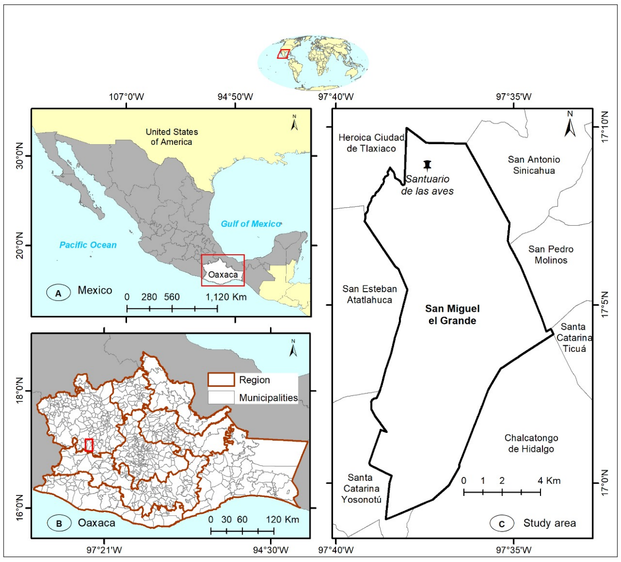

Figure 1. The study area map

2.2 Methodological approach

The methodological approach considers two principal phases: remote sensing analysis with the CCDC algorithm and understanding LUCs with harmonic regression and process tracing. Figure 2 presents the study methodology.

2.3 Data and sources

In this study, we used Landsat data 5,7,8 and 9 level 2, collection 2, Tier 1 acquired from 1993-01-01 a 2024-12-31 to train polygons of vegetation, cropland and bare land classes with local students participation, USFS Landscape Change Monitoring System v2024.10 (USDA Forest Service, 2025) and JRC Global Surface Water Mapping Layers, v1.4 (Pekel et al., 2016) to mask water bodies.

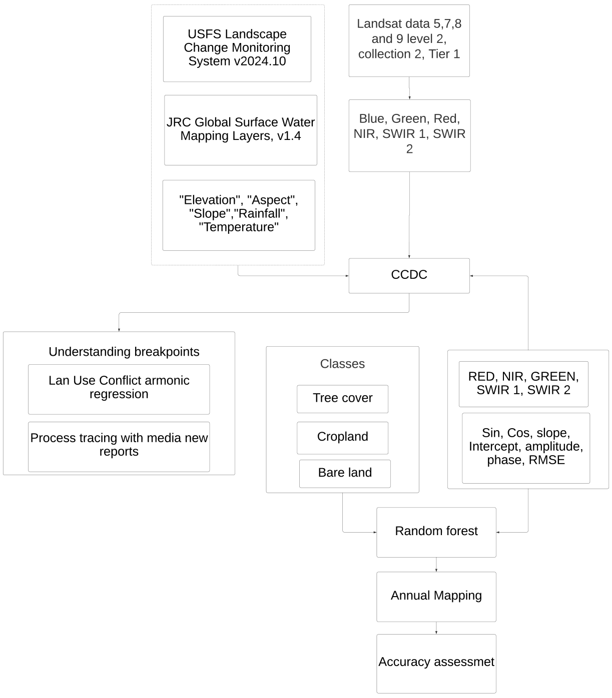

Figure 2. Methodological approach

2.4 Classes

According to the local biophysical characteristics of SMG, participating mapping, and previous literature, three classes to start the Continuous Change Detection and Classification (CCDC) algorithm were defined as follows:

1. **Tree cover**, the principal natural cover; this category involves types of natural and planted forests like pine and oak. The CCDC algorithm can monitor forest dynamics, disturbances, and long trends (Zhang et al., 2022; Nguyen et al., 2025; Jiang et al., 2025)

2. **Cropland**, the principal economic activity is shifting cultivation of native maize. The CCDC algorithm is a practical approach for monitoring shifting cultivation (Chen et al., 2023a,b).

3. **Bare land** includes mainly human assessments, back roads, and mining areas. The CCDC approach can monitor new construction activities (Tang et al., 2024)

2.5 CCDC algorithm

CCDC is a change detection algorithm that utilizes both a change detection mechanism and a supervised classification one to assign a particular LULC to each stable segment. CCDC uses a harmonic model with variable coefficients to fit and predict each band or spectral index of Landsat time series at a pixel level for a given date (Zhu and Woodcock, 2014). First, based on these models, stable segments and breaks are detected, and then a LULC is assigned to each segment. The CCDC algorithm comprises several components, including image preprocessing, continuous change detection, and continuous land cover classification (Zhu and Woodcock, 2014).

Equation (1) shows the CCDC harmonic regression model.

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$$\begin{aligned}\hat{p}(i,t)_{\textit{fitted}} = a_{0,i} &+ a_{1,i}\cos\left(\frac{2\pi}{T}x\right) + b_{1,i}\sin\left(\frac{2\pi}{T}x\right)\\ &+ a_{2,i}\cos\left(\frac{4\pi}{T}x\right) + b_{2,i}\sin\left(\frac{4\pi}{T}x\right)\\ &+ a_{3,i}\cos\left(\frac{6\pi}{T}x\right) + b_{3,i}\sin\left(\frac{6\pi}{T}x\right)\end{aligned} \tag{1}$$

where $x =$ Julian date.
$i =$ The ith Landsat band or vegetation index.
$T =$ Number of days per year (i.e., 365).
$a_{0,i} =$ Coefficient for the overall value of the ith Landsat band or vegetation index.
$S_i =$ Coefficient for inter-annual change.
$a_{1,i}, b_{1,i}, \ldots =$ Coefficients for intra-annual change.
$\hat{p}(i,t)_{\textit{fitted}} =$ Predicted value for the ith band at Julian date x.

The bands considered for spectral classification were Blue, Green, Red, NIR, SWIR1, and SWIR2. The CCDC coefficients were RMSE, intercept, Slope, and Phase. Finally, auxiliary bands were elevation, aspect, DEM, rainfall, and temperature.

2.6 Accuracy assessment

The accuracy assessment of satellite image classifications from 2020 to 2023 was conducted using the method proposed by Olofsson et al. (2014) and estimated with the OpenForis Tool in R software (FAO , 2017).

The sample size was estimated using a stratified random sampling approach, as outlined in Equation (2).

$$n = \frac{\left(\sum W_i S_i\right)^2}{\left[S(\hat{\theta})\right]^2 + \left(\frac{1}{N}\sum W_i S_i^2\right)} \approx \left(\frac{\sum W_i S_i}{S(\hat{\theta})}\right)^2 \tag{2}$$

where N = number of units in the ROI
$S\left(\hat{\theta}\right)$: is the standard error of the estimated overall accuracy that we would like to achieve.
W_i = the mapped proportion of area of class i
S_i = the standard deviation of stratum i
$S_i = \sqrt{U_i(1-U_i)}$

2.7 Identification of LUCs' points

Five local Geographic Information Systems students from the University of Chalcatongo identified LUCs points in a workshop in March 2025. First, we discussed agrarian conflicts in SMG and their environmental and social impacts, as well as news and posts on social networks like Facebook. Then, in Google Earth Pro, we discussed the location of LUCs' points. Finally, we generated a KML file with 8 POIs that are useful to explain the causal relationship between LUCs and LUCs. Figure 3 shows georeferenced LUCs' points.

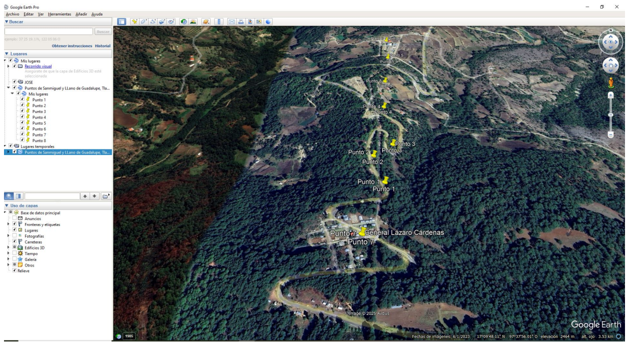

Figure 3. LUCs in SMG.

2.7.1 Breakpoints as a LUCs' points

A breakpoint occurs when the model-fitting prediction differs significantly (more than three times the root mean squared error, RMSE) from the actual observation, anomalous slopes arise, or the first or last observation differs by three standard deviations from the model prediction (Zhang et al., 2022). Then, when a breakpoint occurs, a LUCC is potentially detected.

Breakpoint coefficients were:

1. **tStart** =the start time of one segment
2. **tEnd** =the end time of one segment,
3. **tBreak** = the breakpoint detection time,
4. **Magnitude** of the change from one segment to the next segment.

2.7.2 Explaining with SWIR band

We selected the short-wave infrared 2 (SWIR2) band to identify LUCs. The SWIR2 band spanned approximately 2080 to 2350 nm for Landsat 4 and 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper+ (ETM+). A single SWIR2 band is still used for Landsat 8 and 9 Operational Land Imagers (OLI and OLI2, respectively), but its spectral response has been narrowed (approximately 2110 to 2290 nm) (U.S. Geological Survey, 2022; Lamb et al., 2022). The SWIR band enables continuous monitoring and updating of land cover features through spatial maps, particularly in regions where change and development are rapid (Kumar et al., 2022).

We used Google Earth Engine (GEE) to run the CCDC algorithm. GEE is a cloud-based platform for planetary-scale geospatial analysis that leverages Google's massive computational capabilities to address various high-impact societal issues, including deforestation, drought, disaster, disease, food security, water management, climate monitoring, and environmental protection (Gorelick et al., 2017).

2.8 Process tracing to understand the complex causal relationship between LUCs and LUCC

Process tracing aims to identify causal mechanisms that connect the causes of events or phenomena to their outcomes, drawing evidence from a wide array of sources associated with a single case or a small number of cases (Pickering, 2022). Overviews of process tracing generally emphasize the need to draw on multiple sources of data about decision-making and other political processes, including official documents, media reports, stakeholder interviews, event observation, and ethnography (Bennett and Checkel, 2014), and have been applied to understanding conflicts over marine environments (Boonstra et al., 2023). In this study, we combine new media reports and local knowledge.

3. Results and discussion

3.1 Validation of land cover classification

The results of the confusion matrix are in table 1. Approximately 1,043 sampling points were calculated using the Open Foris Tool (FAO , 2017) and subsequently validated through the use of Google Earth images and local community input.

Year	Accuracy asessment
2020	0.89
2021	0.91
2022	0.90
2023	0.88

Table 1. Results of accuracy asessment.

3.2 Mapping Annual Land use cover

Figure 4 shows the annual land cover every six years. All maps from 1993 to 2023 are available here https://code.earthengine.google.com/a0c0313b8a5b7bfa16304a0efaa05c73

During the study period, we identified an increase in tree cover class and a reduction in cropland and bare land. Similar trends have been identified in Mixteca Alta Geopark, known as forest transitions (Lorenzen et al., 2020; Lorenzen, 2022; Hernández-Aguilar et al., 2021).

3.3 Understanding LUCs as a breakpoint in CCDC harmonic regression

The scientific literature in Mixteca Alta region focuses on determinants of forest transition, such as migration, population decline, agricultural land abandonment, and social capital (Lorenzen et al., 2020; Hernández-Aguilar et al., 2021), but LUCs are not documented. We tested the eighth LUC points on harmonic regression and identified a more explicit breakpoint in Santuario de las Aves as a case study.

Santuario de las Aves is an ecotouristic area that received payments for ecosystem services (PES) (Hernández-Aguilar et al., 2017). PES is an incentive-based instrument for natural resource management that provides economic incentives for landowners, conditional on either the direct provision of ecosystem services or a specific resource management activity (Izquierdo-Tort et al., 2025). Near this place, confrontations occurred between the inhabitants of Llano de Guadalupe Tlaxiaco and SMG due to a dispute over 2,300 hectares of forest. Figure 5 shows the Facebook page; the last post was on August 18th, 2022.

The CCDC harmonic regressions on pixels of LUCs. The identification of breakpoints corresponds to the occurrence of LUCs. Figure 6shows the harmonic regression for the SWIR2 band in a pixel of the natural area called the Santuario de las aves. It is possible to identify a breakpoint between the two segments, red and yellow, in 2023. The surface reflectance change from 0.08 to 0.16 is due to human actions and vegetation loss.

3.4 Understanding land use conflict based on news reports

Process tracing with new reports is a tool for better understanding LUCs. According to local authorities, Comisariado de Bienes Comunales, the main aggressions of Llano de Guadalupe Tlaxiaco were on May 5th and November 22nd to Lazaro Cardenas in SMG, where five people died: two agents of the State Investigations Agency (AEI), two police, two municipal agents, and a community member (Fiscalia General de Oaxaca, 2023). The expressions of LUCS have included casualties, illegal logging, forest fires, and housing fires, which lead to biodiversity loss, soil erosion, and the infiltration of rainwater (H. Ayuntamiento Constitucional de San Miguel El Grande, Tlaxiaco, Oaxaca, 2023). Figure 7 shows two photos provided by the community people to the poderlatam website (Contreras and Balderas, 2024). These LUCs' photos show social and environmental impacts on LS.

The state government reported the presence of illicit activities such as drug trafficking, arms trafficking, and illegal logging (Miranda, 2023). These drivers have been incorporated into land use change models (Tellman et al., 2020). Recently, the government announced the solution of LUCs; the Santuario de las Aves will be registered as a protected natural area in the Comision Nacional de Áreas Naturales Protegidas, and a military cuartel (Guardia Nacional in México) will be created (Badillo, 2024).

Therefore, it is essential to examine other global causes with local community impacts, as people in this region are migrants in the USA due to telecoupled changes that can be better explained through a telecoupling framework (Martín-López et al., 2019), as seen in studies in the European Arctic (Živojinović et al., 2024).

4. Conclusion

We identified a forest natural revegetation process, where cropland and bare land were diminished. It is necessary for more scientific research to explain this process in SMG.

This study employs Landsat time series analysis, combined with the CCDC algorithm and process tracing, to assess the impact of human activities on land system changes. The harmonic regression coefficient provides useful information; for example, the start and end times, as well as the magnitude, can be interpreted as a metric of impact.

Data from Landsat time series analysis is a source to explain LUCs, considering the stages: pre-conflict, conflict, and post-conflict in a harmonic continuous model and with land use/cover annual maps. The information generated can help forest community monitoring and decision makers to address the solutions of LUCs in in rural communities.

5. Limitations and future research

In this study, only one breakpoint of LUC was explained in more depth. A more in-depth analysis is necessary in the study area. We defined only three general classes; in future research, we can be more specific and only consider new reports as tracing processes.

For future research we are considering to explore advances in near-real time forest change monitoring systems with CCDC algorithm and Sentinel data, for example such as experiences in Madagascar (Bullock et al., 2022) with Sentinel 1 radar, in Portugal with Sentinel 2 provided timely change detection with high spatial detail for continuous forest loss monitoring (Moraes et al., 2024), Landsat and Sentinel 2 data harmonized to detect disturbances around the world (Li et al., 2025). Additionally, it will be possible to integrate more remote sensing data

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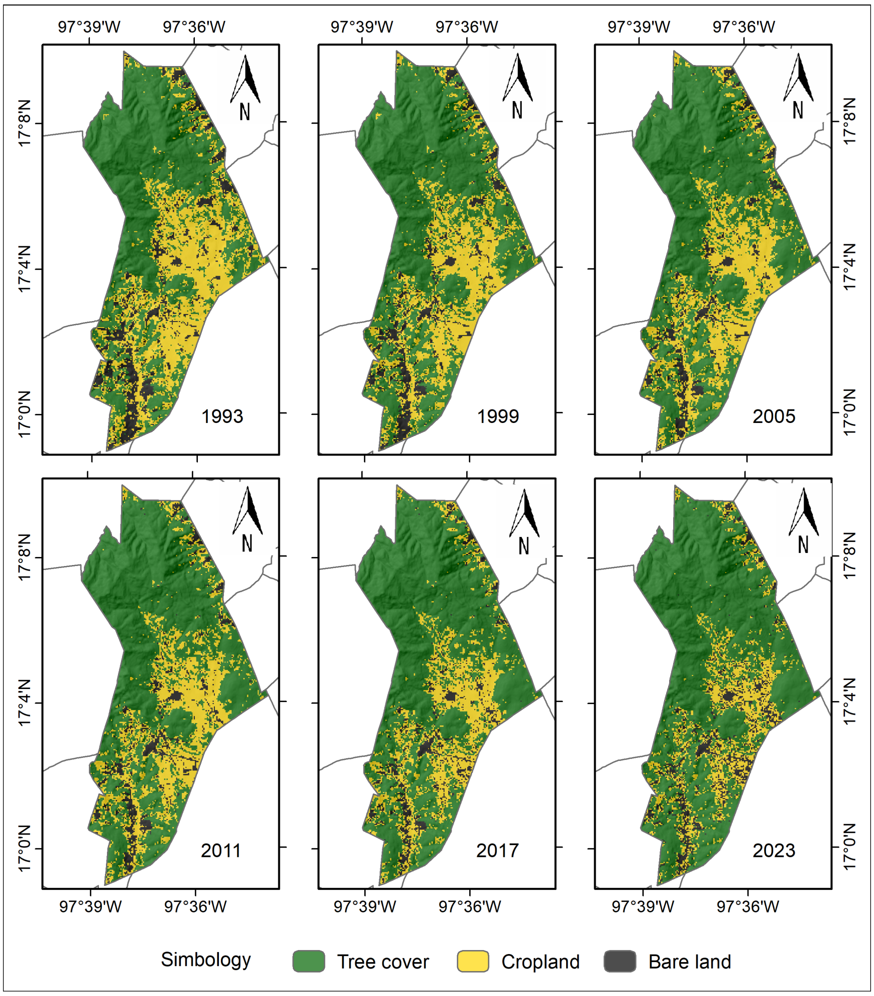

Figure 4. LULC Annual classifications in SMG

Figure 5. Santuario de las Aves Facebook page.

available for land cover mapping with socio-economic data and qualitative methodologies, such as interviews and workshops with different stakeholders, to analyze LS as a complex and multifaceted problem *(wicked problem)*.

6. Acknowledgments

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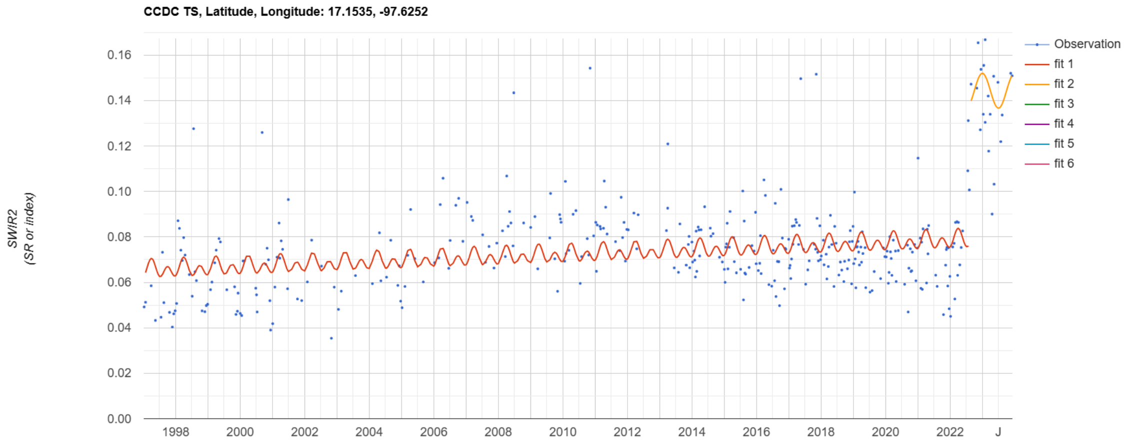

Figure 6. Harmonic regression in Santuario de las aves.

Figure 7. Photos of LUCs (Contreras and Balderas, 2024)

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