Deforestation risk model for the state of Chiapas

Project: Use of Earth observation platforms to support the implementation of climate change mitigation goals in the forest sector and land use change in three states of Mexico

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Edith Mondragon Vazquez
Miguel Angel Castillo-Santiago
Robert de Jesús Domínguez Vera
Richard Tipper

El Colegio de la Frontera Sur (ECOSUR)
& Ecometrica LTD

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1. Introduction

As part of the activities of the UK-PACT Mexico project and at the request of the state government, ECOSUR's Earth Observation Department developed a spatially explicit model of deforestation risk for the state of Chiapas. The purpose was to provide information to identify areas at greatest risk of forest loss to help direct resources and efforts. The resulting risk map can also be used as a reference level against which the performance of future REDD+ projects can be estimated. The ultimate goal is to contribute to public and private efforts to prevent further growth of the agricultural frontier and the loss of remaining forests and other natural ecosystems.

This deforestation risk map was prepared using deforestation statistics for the period 2005-2019 developed by the same department and incorporates a series of spatial variables related to the deforestation process. The result is qualitatively represented in five levels or classes of deforestation risk, from very low to very high. For each risk-class, the expected future rate of loss for the next 5 years was projected, based on changes observed in the past 5 years.

This document presents in detail the inputs used, the methodological process and the deforestation risk map of the state of Chiapas.

The deforestation risk map and associated maps are available in the following online application: https://bosquesysubsidios.ecosur.ourecosystem.com/interface/

2. Materials and methods

2.1. Context and model inputs

Chiapas is a state containing a great diversity of landscapes, micro-climates, vegetation types and rural livelihood systems. The risk modeling approach seeks to accommodate this diversity and its influence on land use change processes in different parts of the state.

The risk model used, as inputs, vegetation and land use maps for 2005, 2015 and 2019 prepared by ECOSUR's Earth Observation Department[1] with support from the UK Space Agency's *Forests2020* project. These high fidelity EO-derived products are of approximately 1:40,000 scale, with 36 thematic classes including forest types and their level of disturbance, and disaggregated land use classes in rainfed agriculture, irrigation, pastures, agricultural and forestry plantations. The construction of these maps used high-resolution satellite images from SPOT, RapidEye and Sentinel-2, along with extensive ground-based surveys for calibration and validation.

Other geospatial inputs included a Digital Elevation Model (DEM)[2], the limits of the Protected Natural Areas (ANP)[3], climatology and soil-influencing geology. The map of climate types was developed by García (2004).

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[1] Full name is "Department for the Observation and Study of the Land, Atmosphere and Ocean"
[2] National Institute of Statistics and Geography (INEGI - www.inegi.org.mx/app/geo2/elevacionesmex)
[3] National Commission for Protected Areas (CONANP - sig.conanp.gob.mx/website/pagsig/info_shape.htm)

2.2. Model Approach

The model was based on the delineation of landscape units containing relatively homogeneous sets of landform, climate, and predictive variables for deforestation. The predictive variables included the degree of forest fragmentation and historic land use change as well as landscape factors mentioned above.

An exploratory analysis using linear correlations was carried out for the preliminary selection of predictors. Details of the processes used in the development of these inputs are given below.

2.2.1 Delineation of Landscape Units

The first step involved delineation of relatively homogeneous physical-geographical landscape units (LUs) or natural territorial complexes. These are areas extending over the same geological basement, or sedimentary mesoform, with a similar micro-climate. The homogeneity in these units strongly influences the distribution of vegetation and soils (Priego et al., 2004). The delineation of the LUs, based on a method proposed by Priego et al. (2010), involved the following steps:

1. Semi-automated construction of a map of relief units from the vertical dissection and subsequent manual adjustment through visual interpretation. This step used the INEGI digital elevation model of 15 m resolution.
2. Adjustment of the climate map generated by García (2004); using the climatic regions of Vidal-Zepeda (2005) and the climatic stations of Chiapas.
3. Grouping of the rock type map, according to their geologic origin.
4. A spatial combination was made between the vector layer of relief units and climate types. The spatial coherence of this combination was reviewed, and minimal areas were eliminated, giving priority to relief since its original scale is finer.
5. The result of the previous process was combined with the rock type map, in this case the units were not further divided, only the name of the rock that predominates was assigned.
6. Each unit was assigned a unique identifier, and a legend was created in hierarchical order, based on origin, climate, relief, and geology.

2.2.2 Mapping of Historic Deforestation

The 36 thematic classes of the vegetation and land use maps were grouped into two general classes, forest and non-forest. Secondary forest (secondary arboreal vegetation) and agroforestry systems were also included in the forest class, but not shrubby vegetation, since this vegetation class often corresponds to fallow agricultural areas. Following this logic, changes from forest to agricultural and livestock use, human settlement and secondary shrub vegetation were considered as deforestation.

2.2.3 Variables Related to Deforestation

Following a review of historic research on the dynamics of land cover change in Chiapas, along with a review of previous risk mapping methods, key spatial variables were identified that could be related to change processes. These included indicators of accessibility (distance to roads, distance to agricultural areas and slope), of forest fragmentation, level of protection (whether the forest lies within a natural protected area) and the dominant type of agricultural production within the region.

The Euclidean distance to roads (paved and unpaved roads) and agricultural areas (rainfed agriculture, pastures and herbaceous vegetation) was calculated. The slope of the terrain was also derived using the DEM. The continuous values of distance to roads slope were grouped into ordinal classes. The optimal number of classes was estimated with the *elbow method,* which is based on the sum of the squares of the distances of each element of the data with its corresponding centroid (Cui, 2020). The class size was calculated using the natural break method (Jenks & Caspall, 1971); which has the characteristic of minimizing the variance within the classes and maximizing the difference among them.

To calculate the forest fragmentation statistics, the following indexes were calculated for each LU: Shannon diversity index (SHDI), edge density (ED), and proportion of the total landscape composed of the largest patch index (LPI) using the Python library "*PyLandStats*" (Bosch, 2019). SHDI, refers to the number of classes present in the landscape, as well as the relative abundance of each class; the SHDI approaches 0 when the entire landscape consists of a single patch, and approaches its maximum value as the area distribution between classes becomes more equal. ED is a sum of edge lengths dependent on a single class type based on the total area converted to one hectare for analysis, equaling 0 when the entire landscape and its edges consist of the corresponding patch class (McGarigal & Marks, 1994). The LPI approaches 0 as the largest patch gets smaller and approaches its maximum value when the area of that patch equals that of the entire landscape.

It has been observed that land use changes within natural protected areas (NPA) are sometimes related to the type of land use "allowed" in each of its zones (zoning results from the management plan of the NPA). Depending on the category of each NPA, the following management policies or zoning were observed: a) core zone (protection), b) core zone (restricted use), c) buffer zone and d) buffer zone (with human settlements, exploitation, and other uses). In this sense, we evaluate deforestation levels within the NPA zones.

Finally, each landscape unit was classified according to its type of predominant land use, that is rainfed agriculture or pastures (livestock activity).

2.2.5 Calibration of the spatial model of deforestation

The explanatory variables and their relationship with the deforestation patches, were used to generate a spatial model using the DINAMICA EGO software to identify the areas most likely to be deforested.

The principle used by DINAMICA to estimate the areas most prone to change is called Weight of Evidence. This is a quantitative Bayesian method that allows combining empirical evidence in favor of a hypothesis. In this case, the proposed hypothesis is that deforestation is more likely to occur in the most accessible or fragmented forests, or those that present the lowest level of government protection (outside ANP or in buffer areas) or that are located in regions where livestock land uses predominate. The methodology calculates empirical relationships of the spatial variables, represented by the categorical maps, with respect to deforestation and evaluates the predictive power of each category of the variables used. The calculated weights of evidence are simultaneously combined into a single equation for the probability of deforestation calculation. The result is a model with continuous values that for practical purposes was grouped into four categories.

2.2.6 Fitting the Model using Historical Trends

Spatial patterns of deforestation can change over time, however in some areas due to the strength of causal factors these patterns remain constant. In order to capture this situation, a map of “historical” deforestation trends was used to fit the model obtained by DINAMICA. The map of historical trends shows a categorization of the landscape units according to the percentages of annual deforestation observed in 14 years (five classes). Note that the spatial model obtained by DINAMICA only captures the pattern observed in the last four years (2015-2019), while the historical trends cover a longer period (2005-2019). We combined both two layers and regrouped the resulting data into five classes as outlined in Table 1.

Table 1. Multiplication between the values of the probability of change map and historical deforestation. Colors indicate deforestation risk levels.

Probability of deforestation/historical deforestation	**1 (low)**	**2 (medium)**	**3 (high)**	**4 (very high)**
1 (very low)	1	2	3	4
2 (low)	2	4	6	8
3 (medium)	3	6	9	12
4 (high)	4	8	12	16
5 (very high)	5	10	15	20

2.2.7 Estimation of expected deforestation

Expected deforestation is the proportion of forest that is expected to be lost in a certain period. To estimate this value, the percentage of annual deforestation by landscape, estimated in section 2.2.6, was used; and according to the level of risk, an average value of the percentage of deforestation per year was obtained.

2.2.8. Aboveground biomass

We employed the National Forest Inventory data and the allometric equation of Chave et al. (2014) to estimate the aboveground biomass content of the forests. Because forest composition and structure often vary between physiographic zones, we calculated the average aboveground biomass per forest type in each physiographic region.

3. Results

3.2.1 Landscape units

A total of 1,602 landscape units were obtained with a minimum area of 100 ha. Each one is characterized by the type of geological origin, relief, climate and type of dominant rock. These units were used as analysis zones for fragmentation analysis. The high number of units is a result of the State of Chiapas having varied relief, with a combination of dissected mountains, plains, river valleys and coastal areas.

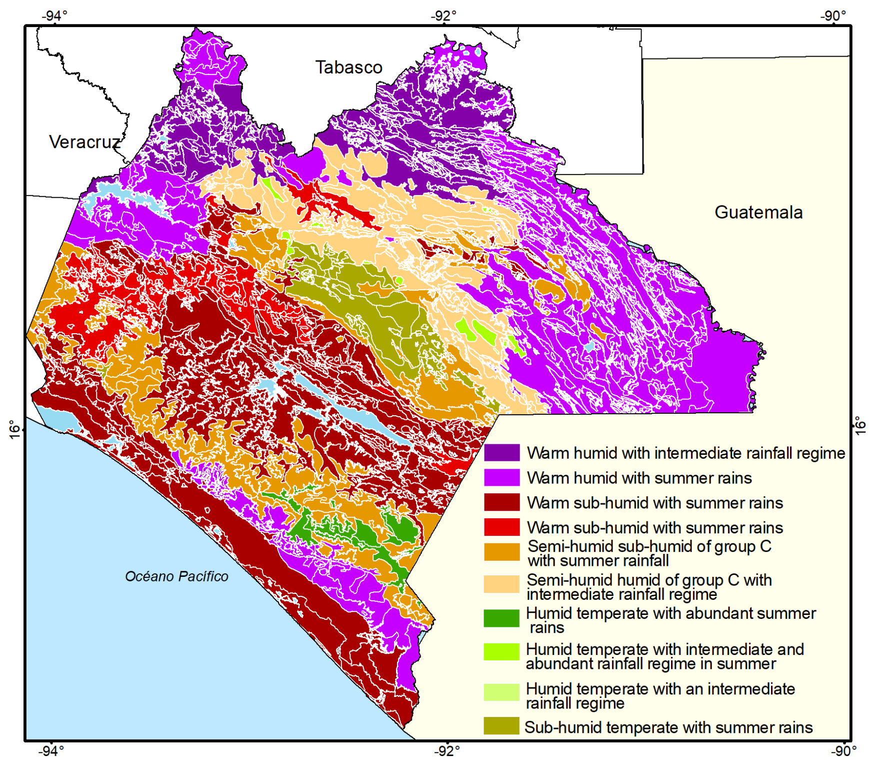

Figure 1. Landscape units represented according to the prevailing climates.

3.2.2 Deforestation

The estimated deforestation for Chiapas from 2015 to2019 was 14,000 ha per year. The regions with the most significant loss of forest cover are the Selva Lacandona and the north of the state.

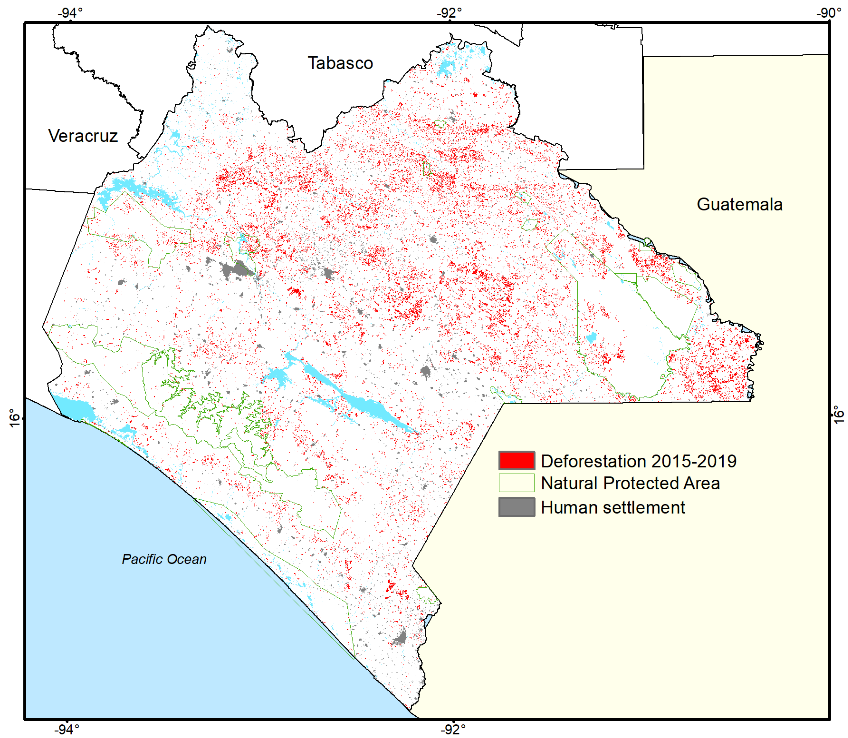

Figure 2. Spatial distribution of deforestation in Chiapas

3.2.3 Relationship between spatial attributes and deforestation

Distance to roads: this variable has a linear relationship to deforestation, with proximity to vehicle accessible roads increasing the probability of deforestation. It is observed that at more than 3 km there is no longer any influence on the process.

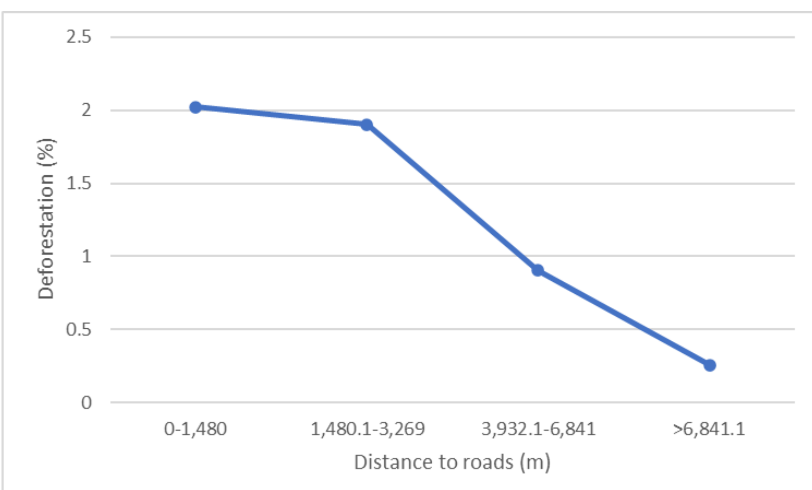

Figure 3. Relationship between distance to roads and deforestation

Slopes: Forests on flat terrain were the most deforested, while those on steep slopes (> 30 degrees) were the least affected

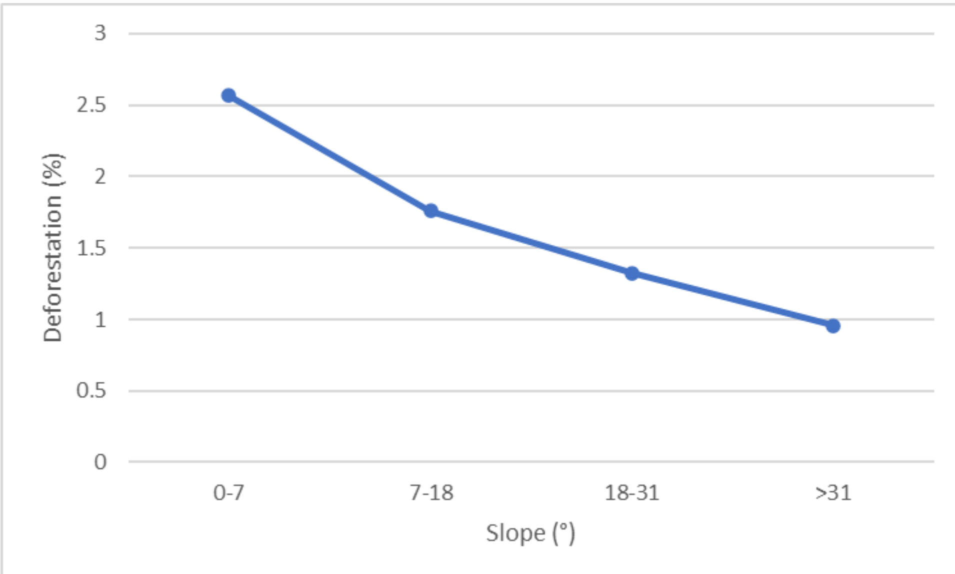

Figure 4. Relationship between terrain slope and deforestation

Distance to agriculture: The forests bordering agricultural areas tend to be susceptible to being lost, due to the expansion process, this is evident in the state, since the areas less than 350 m away are the ones that have lost the largest area of forests.

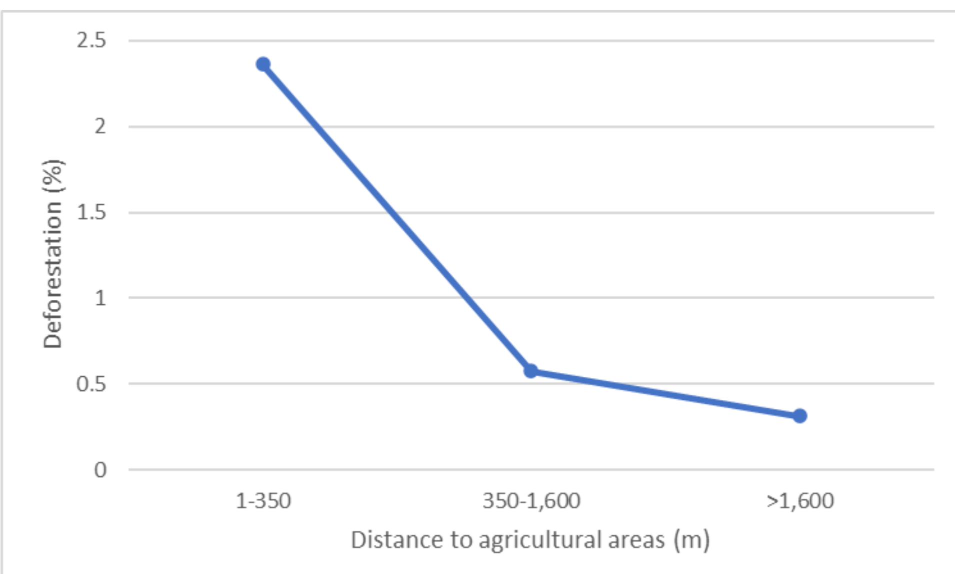

Figure 5. Distance to agriculture.

Diversity (SHDI): It is observed that the landscapes that are made up of a single patch, of either of the two classes: forest or agricultural, have less deforestation, while those that are more diverse, that is to say, that have a similar number of patches of both classes, have less deforestation. further deforestation.

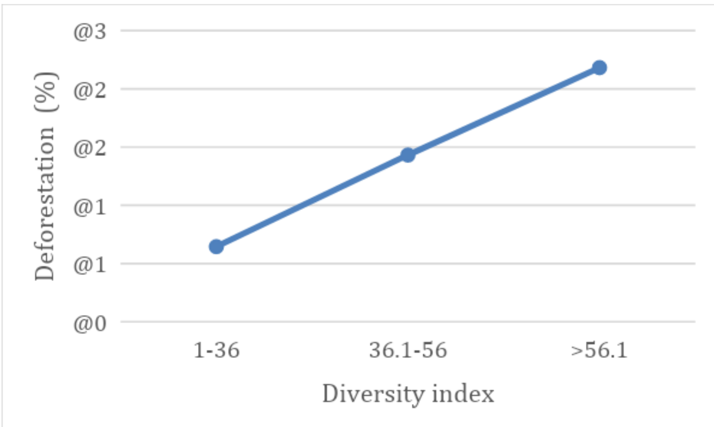

Figure 6. Fragmentation index (Shanon diversity) and deforestation

Edge Density (ED): The areas with the highest edge density are the most fragmented and also those with the largest deforested area.

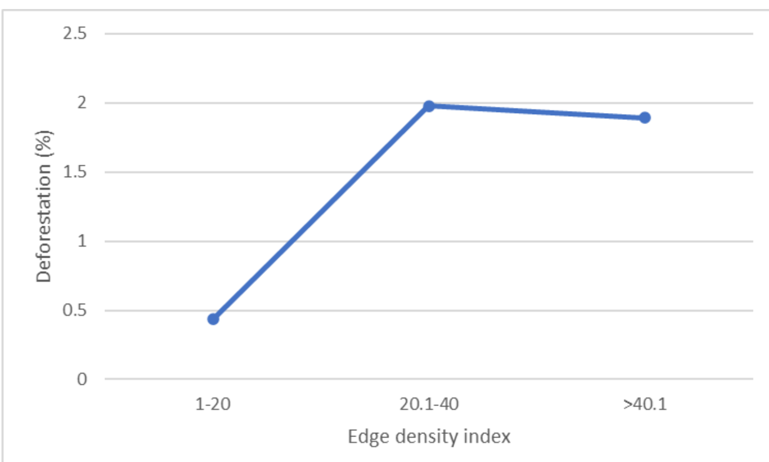

Figure 7. Fragmentation index (edge density) and deforestation

*Proportion of the total landscape made up of the largest patch. Large_patch_index (LPI):*represents the size of the largest patch of forest within each landscape. In landscapes with large forest patches there is less deforestation, while landscapes with forests in different patches increase deforestation.

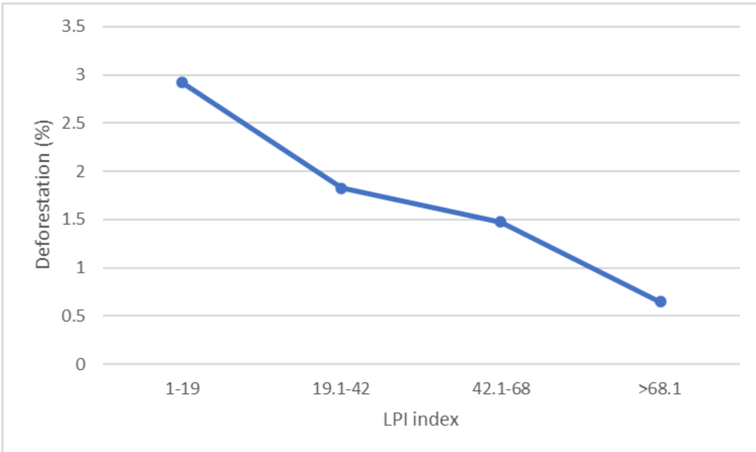

Figure 8. Fragmentation index (Proportion of the landscape occupied by the largest fragment) and deforestation.

Natural Protected Areas (NPA) zoning. It is observed that the zoning of NPAs has implications for the intensity of changes in land use, i.e., areas with more significant restrictions on human activity, for example, the core zones, show low levels of deforestation, but it is in the buffer zones, where sustainable activities or recreational uses are allowed, that the greatest loss of forest occurs.

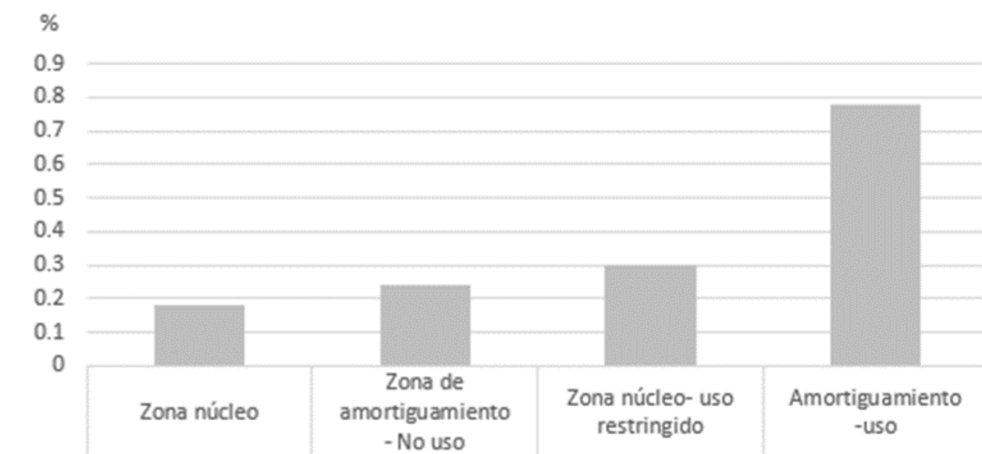

Figure 9. NPA zoning and deforestation.

*Forest conservation level***:** Most of the state's forests are secondary, that is, they are young or highly disturbed forests. It is observed that those where there is a greater quantity of mature or primary forests, the deforestation process is less. As in the Selva Lacandona, and the Sierra Madre.

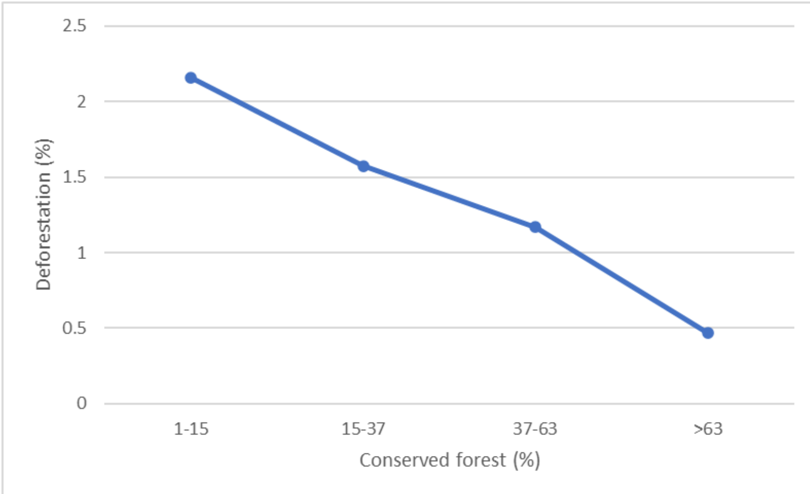

Figure 10. Landscapes with a greater presence of conserved forests and deforestation vs. deforestation

Main productive activity: Livestock and agriculture are the main causes of deforestation in the state, and their dominance in each of the landscapes has a different influence on this process. It is observed that the landscapes with the highest livestock activity are those with the largest deforested area.

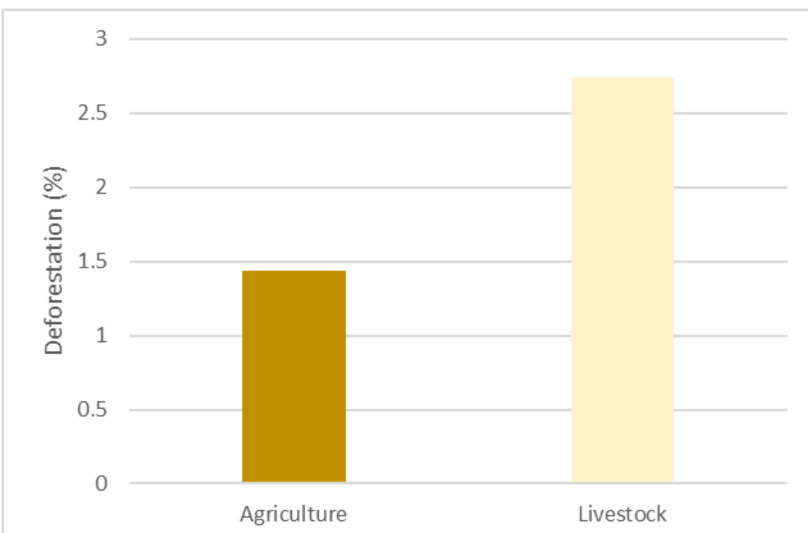

Figure 10. Predominant productive activity and deforestation

3.2.5 Deforestation risk model

The output of the model was the deforestation probability map. This map shows the sum of the weights of each explanatory variable. It shows areas with low, medium, high and very high probability. The results highlight the influence of accessibility and fragmentation variables, leaving areas with low accessibility and little fragmentation as regions with low risk of deforestation.

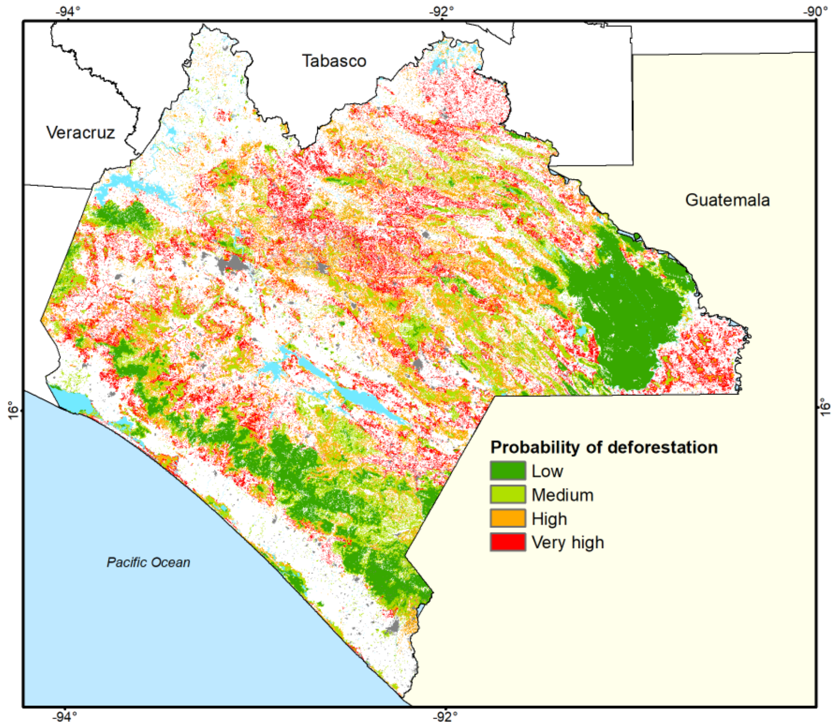

Figure 11. Deforestation risk map of the Chiapas state.

3.2.6 Fitting the probability of change model

By including historical deforestation statistics by landscape, it was possible to adjust the map of probability of change, especially in those areas that were at high risk due to accessibility issues, but that in the last 14 years their deforestation was low. Likewise, the region of Marqués de Comillas was distinguished, whose deforestation process is particularly high compared with other regions of the state.

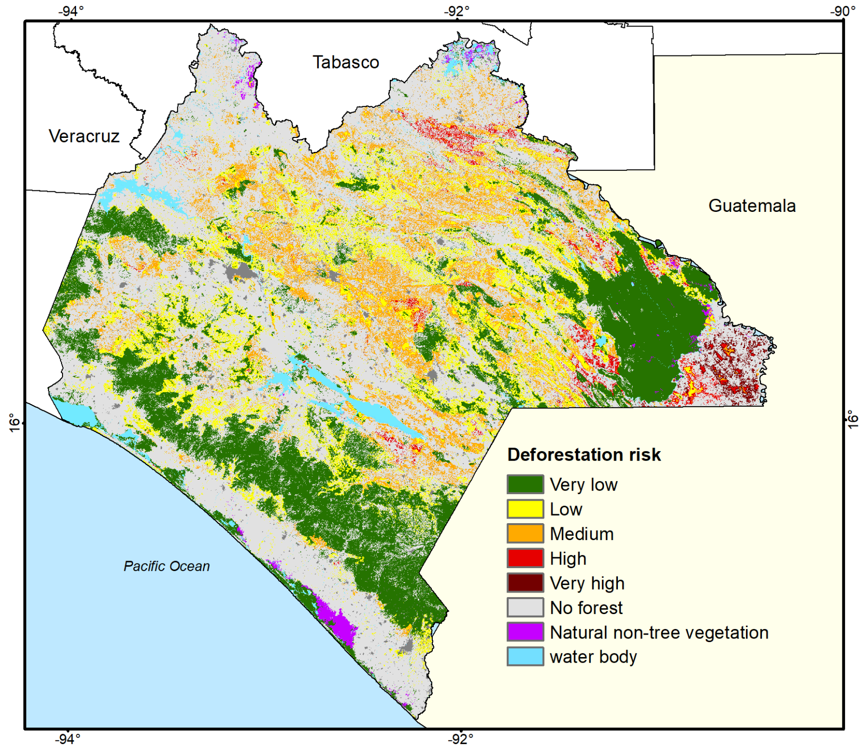

Figure 12. Deforestation risk map of the state of Chiapas.

Areas with high and very high values are found in the region of the Lacandon rainforest and more markedly in the subregion of Marqués de Comillas where the main type of vegetation is high evergreen forests, the medium level of risk is It is concentrated in the pine-oak forests and low deciduous forests, located in the central zone of the state. The forests with a very low level of risk are found throughout the Sierra Madre and the ANP's of Ocote and Montes Azules (table 4).

Table 4. Type of vegetation by level of risk in the state of Chiapas

	Risk level				
Land cover	**Very low**	Low	Medium	High	Very high
Cloud forest	47,762	8,901	5,105		
Secondary Cloud forest	60,890	19,243	4,752	11	
Pine-Oak forest	119,008	35,897	23,277	713	
Secondary Pine-Oak forest	250,588	198,913	149,534	5,046	1

Disturbed Pine-Oak forest.	87,374	38,029	18,348	218	
Tropical moist forest	431,479	99,292	74,306	23,056	13,446
Secondary tropical moist forest	216,571	203,053	204,646	46,013	21,239
Tropical dry forest	68,355	92,385	105,968	5,086	18
Mangrove	52,132	3,380	235	90	
Grassland	5,860	36	215		
Riparian vegetation	5,966	15,022	31,061	464	439
Coffee agroforestry system	116,336	30,173	11,749	52	
Total	1,462,321	744,324	629,196	80,749	35,143

3.2.7 Estimation of expected deforestation (five years projection)

The expected deforestation for each level of risk is shown in table 5. An expected deforestation percentage of 0 was obtained for the areas with the lowest level and 2.5 for the areas with the highest level of risk, the latter is only presented in the municipalities of Marqués de Comilla and Benemerito de las Americas.

Table 4. Percentage of expected deforestation by risk levels

Key	***Class***	***Annual percentage***
1	Very low	0.0
2	Low	0.3
3	Medium	1.0
4	High	2.0
5	Very high	2.5

To illustrate the magnitude of expected losses from the risk map and its associated deforestation rates, we estimated possible deforestation over the next five years using elementary assumptions. Under a BAU scenario, conserved and secondary evergreen forests are expected to have the most significant areas of deforestation, with approximately 30,000 ha. Secondary pine-oak forests would follow this, and deciduous forests with expected deforestation of 10,000 and 7,000 ha, respectively (Table 5)

Table 5. Projected feature loss of forest biomass from vegetation types in Chiapas from 2022 to 2026

Land cover	Area (ha)	Aboveground biomass (t)
Cloud forest	389	33,462
Secondary cloud forest	527	44,793
Pine-Oak forest	1,773	192,533
Secondary Pine-Oak forest	10,965	948,588
Disturbed Pine-Oak forest	1,510	100,393
Tropical Moist forest	9,191	1,311,818
Secondary Tropical moist forest	20,535	1,731,879
Tropical Dry forest	7,195	268,764
Mangrove	71	6,006
Coffee agroforestry system	1,045	59,487
Total	53,201	4,697,722

The biomass contents of vegetation types can vary between physiographic regions, so deforestation areas do not correspond directly to the total biomass. We can see from table 5 that unless the remaining risks are addressed future deforestation may still be relatively high with significant greenhouse gas emissions.

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