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Assessing and modeling the impact of land use and changes in land cover related to carbon storage in a western basin in Mexico

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ABSTRACT

In this study, we analyzed the land use and land cover (LULC) change in a hydrologic basin in the western coast of central Mexico and its regional variation in carbon storage. Three thematic maps (1986, 2001 and 2017) were produced by using pixel-based unsupervised classification techniques of Landsat images. LULC maps for 2017, 2033 and 2050 were modeled using a Cellular Automata Markov chain, validating their predictive power using Kappa variations. The InVEST software was used to estimate the carbon stored in four reservoirs, analyzing their variations over time (1986–2050). Accuracy assessment for the classifications revealed satisfactory results with an Overall accuracy of 83% and a Kappa coefficient of 0.76. Results show that the main landscape modifier was the exposed soils class increasing by 65% its extent in 1986, with a net increase around 87,900 ha. The evergreen forest (EF) and the tropical dry forest (TDF) classes showed a decrease along the period analyzed, displaying a net loss of 57,200 ha and 47,200 ha, respectively. Projected land cover changes followed the same trend observed, with a decreasing tendency in the EF and TDF coverages as consequence of exposed soil class increase. This change implies a reduction in the estimated total carbon stock, decreasing from 362.9 Tg C in 1986, to 336.2 Tg C in 2017. According to our model, if the trend detected in this analysis continues, it is expected a reduction to 317.9 Tg C in 2050. This approach combining Cellular Automata and Markov chain analysis with the InVEST model provides elements to estimate changes on carbon storage resulting from landscape changes. It also allows the identification of potential changes in the selected land use classes, providing with technical elements that could help to decision makers to better maintain the ecological integrity of the drainage basin.

1. Introduction

With the increase of greenhouse gases (GHG) emissions, particularly atmospheric carbon dioxide from fossil fuel combustion, there is a growing concern about global changes and problems associated with the carbon sequestration potential of several ecosystems (Eid and Shaltout, 2013). Carbon sequestration in forest ecosystems is one of the most important service provided by these ecosystems, accumulating about 40% of the carbon stored as terrestrial biomass (Dixon et al., 1994), as a result of the 30–50% of the terrestrial productivity occurring there (Phillips et al., 1998).

As suggested by Pan et al. (2011), forest ecosystems are the main storage of terrestrial carbon, since they store 861 Pg C at worldwide level. This large carbon store is divided into different components: 383 Pg C (44%) in soil (at 1 m depth), 363 Pg C (42%) in live biomass (above and belowground), 73 Pg C (8%) in deadwood and 43 Pg C (5%) in litter. However, this distribution depends on the type of biome, the composition of species, the conditions of the site, the degree of disturbance and the intensity of use (Dixon et al., 1994; Pan et al., 2011; Adams et al., 2018).

Concerning this, there are many studies at a worldwide scale, as reported in the meta-analyzes conducted by Dixon et al. (1994), Phillips et al. (1998), and Pan et al. (2016). One of the most recent contributions (Poorter et al., 2016), refers to the geographical and climatic variation in carbon sequestration potential during forest regrowth. It is evident that these studies have improved our understanding of the global carbon cycle, reducing discrepancies in the global carbon budget. Also in Mexico, the number of studies on this subject has increased in the last decade (Dai et al., 2014, 2015; Verduzco et al., 2015). In addition, Paz et al. (2017) published the most recent national

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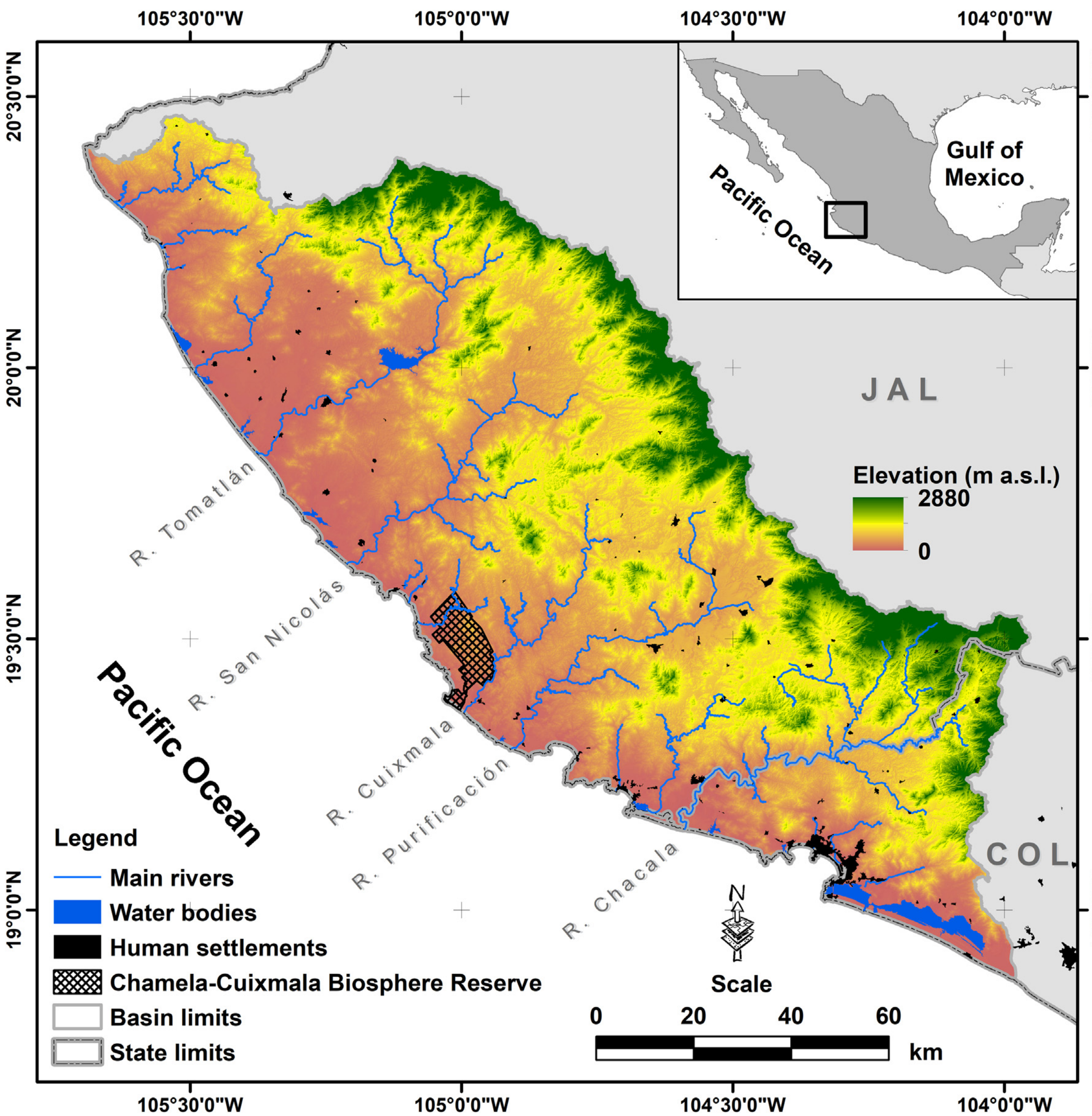

Fig. 1. Geographic location of the study area (hydrologic basin number 15 – Costa de Jalisco). Human settlements correspond to those with 5000 or more inhabitants.

and regional synthesis of the knowledge of the carbon cycle in this country, as part of the strategy to develop models that can be fitted to the reality of the available information, which is scarce and incomplete, even to parameterize simple models of the carbon dynamics.

This review also highlights that most of the research on carbon sequestration in terrestrial ecosystems has been concentrated in tropical rainforests, for which the evidences or baseline are well established. Despite this, few data on the tropical dry forest (TDF) have been included in those analyzes, as a consequence of the scarcity of data on the dynamics of C in these ecosystems. This lack of information is mainly attributed to the fact that their analysis requires a different approach, related with the phenology of this vegetation type (Sanchez-Azofeifa et al., 2013).

Given that forest ecosystems can contribute significantly to regulate the abundance of CO_2 and other GHGs to mitigate global warming, perturbations in this ecosystem could result in a significant change in the global carbon cycle. Therefore, the effective analysis and monitoring of land use and land cover (LULC) changes have been recognized as one of the major concerns for landscape planners and researchers, because of the influence that they have on global environments (Araya and Cabral, 2010; Subedi et al., 2013; Pechanec et al., 2018). Regarding this, scenario analysis is often integrated into studies about land use change (Liang et al., 2017), and given the complexity and uncertainty on the future LULC change, it is necessary to develop models to evaluate future of carbon storage under different land use change scenarios (Von Thaden et al., 2018).

Monitoring and projecting the land use changes are difficult and require a substantial amount of data about the Earth's surface (Li et al., 2007), that only can be achieved through the analysis of Remote Sensing (RS) data and using Geographic Information System (GIS) tools (Araya and Cabral, 2010). RS provides an excellent source of data, from which updated LULC information and changes can be extracted, analyzed, and simulated efficiently, allowing researchers to integrate different models, such Markov chains, to make predictions of landscape changes effectively (Kundu et al., 2017).

Here, integrating some of the above technical elements, the identification of LULC patterns and their temporal changes are analyzed at a basin scale in the Pacific Slope of Mexico, between 1986 and 2017, with particular emphasis in the dry forest ecosystem. Despite being considered as one of the most studied tropical dry forests in the Americas (Sánchez-Azofeifa et al., 2009), almost all studies of the distribution of vegetation and plant species in the coast of Jalisco have been restricted to the Chamela-Cuixmala Biosphere Reserve and surrounding areas (e.g., Suazo-Ortuño et al., 2008; Portillo-Quintero et al., 2013; García-Guzmán et al., 2016; Fraga-Ramírez et al., 2017). There are few studies at a watershed or coastal zone scales in the area (Cotler and Ortega-Larrocea, 2006; Martínez-Harms et al., 2016; Sánchez-Azofeifa et al., 2009), mostly involving the use of remote sensing techniques to derive land use maps, but none of them has estimated carbon sequestration potential at a regional scale. This lack of information complicates the implementation and monitoring of sustainable management and conservation plans in the study area (Von Thaden et al., 2018).

We performed detailed LULC maps for the coastal zone of the states of Jalisco and Colima, Mexico over three decades in order to determine past changes and the current extent of different land uses. That information was used to model future scenarios of modification and use the estimated trends to predict changes in carbon storage over time (1986–2050). This study provides an invaluable information for carbon stock baselines at a basin scale, with a methodology replicable for landscapes with similar settings.

2. Study area

The study area corresponds to the hydrologic basin number 15 – Costa de Jalisco, located on the west coast of Mexico, covering part of the states of Jalisco and Colima (between 18° 49′ to 20°30′ N Latitude, and 103°50′ to 105°50′ W Longitude), encompassing a total area of 12,967 km^2. The study area is characterized by having a very marked seasonality (almost 80% of rainfall occurring between June and October) with an annual precipitation of 1144 mm, and a mean annual surficial runoff of 3606 hm^3 per year (INEGI, 2000). There are five main rivers in the region that are considered as underdeveloped due to the proximity of the mountains to the coast (Fig. 1; INEGI, 2000).

The highly heterogeneous landscape of the region has promoted not only a high diversity of species belonging to several taxonomic groups but also a high beta diversity, which indicates high levels of endemism and local patterns of diversification, especially in the central part where the Chamela-Cuixmala Biosphere Reserve, a protected area of 131 km^2 of well-preserved tropical deciduous forest is located (Balvanera et al., 2002; Cotler and Ortega-Larrocea, 2006; Suazo-Ortuño et al., 2008; Avila-Cabadilla et al., 2012). Despite the tropical deciduous forest is widely distributed across the American continent, Mexico has the greatest extension, represented by 38% of the total area of this ecosystem in the continent (Portillo-Quintero and Sánchez-Azofeifa, 2010). It is mainly located in lowlands of western Mexico bounded by the Pacific Ocean and isolated from central Mexico by the mountainous system of the Sierra Madre Occidental and Sierra Madre del Sur. According to Sánchez-Azofeifa et al. (2009), most of the coast of Jalisco is represented by this ecosystem, followed by evergreen forests and extensive areas that include agricultural fields and pastures.

3. Methods

3.1. Landscape changes

Landscape changes were analyzed from land use and land cover (LULC) maps derived from the classification of satellite images acquired by Landsat 5 Thematic Mapper (1986), Landsat 7 Enhanced Thematic Mapper Plus (2001) and Landsat 8 Operational Land Imager (2017), obtained through the USGS Global Visualization Viewer. All images were captured during the dry season, when phenological characteristics of the main vegetation types allow a good discrimination. Three satellite images by date with Path-Row: 29–47, 30–46, 30–47 were used to cover the study area.

The basin limit was downloaded from the Flow Simulator in Drainage Basins (SIATL) scale 1:50,000 from the National Institute of Statistics and Geography (INEGI, by its Spanish acronym) of Mexico. The study area was isolated from each scene by a mask produced by the rasterization of the basin limits vector. All scenes were individually classified by using K-means unsupervised classification algorithm, run in IDRISI TerrSet software (Eastman, 2016). The classification scheme covered the following LULC classes: aquatic surfaces (AS), evergreen forest (EF), tropical dry forest (TDF), exposed soil (ES), crops (CR), saltmarsh (SM), mangrove (MN), littoral (LI) and human settlements (HS). This later class was digitized on-screen over false-color composites of satellite images for each date analyzed.

Accuracy of the most recent thematic map was estimated based in control points, obtained by field verifications during 2016 and 2017. In areas where physical access was not possible, we generated verification points from high spatial resolution (1.5 m) satellite images (SPOT7) to accomplish the minimum required sample size. To estimate an adequate overall sample size, the number of sampling points was calculated according to (Cochran, 1977; FAO, 2016) for stratified random sampling following the equation:

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

where N is the number of pixels in the area; $S(\hat{O})$ is the standard error of the estimated overall accuracy that we would like to achieve; W_i is the mapped proportion of the area of class i; and S_i is the standard deviation of the stratum i.

An error matrix was constructed and indicators of the Overall accuracy, the User's and Producer's accuracy, and the Kappa coefficient were derived from this arrangement. Our LULC classification was accepted until it reached an 80% or higher in overall accuracy (Congalton and Green, 2009). Finally, we used a post-classification approach to determine qualitative and quantitative aspects of the changes in the period analyzed. Classification results were compared on a pixel-by pixel basis using a change detection matrix obtained by cross-tabulation (1986–2001, 2001–2017, 1986–2017), where areas of change were extracted (Hernández-Guzmán et al., 2008).

3.2. Scenario modeling and validation

In the last decade, many studies have emerged about projecting scenarios from current rates of change and for carbon modeling (e.g., Galford et al., 2015; Gago-Silva et al., 2017; Thompson et al., 2017). From these studies, DINAMICA EGO system is considered a state-of-the-art land use and cover change model because of its speed and stable computational performance as well as incorporates government policy and other biophysical and anthropogenic datasets (Mas et al., 2013; Soares-Filho et al., 2013; Stan et al., 2015; Adams et al., 2018). However, a recent contribution (Pérez-Vega et al., 2012) compared DINAMICA EGO with another extensively documented land cover change model (Land Change Modeler, LCM in IDRISI). Their results favor LCM over DINAMICA with respect to the overall assessments. The neural networks approach (LCM) seems to be more appropriate for producing maps of overall potential change (Pérez-Vega et al., 2012). Besides, TerrSet includes modules for the analysis and manipulation of spatial data and provides a powerful platform for deriving the data for use in these models.

With the above considerations, LULC scenarios were modeled using Cellular Automata (CA) and Markov chain analysis in IDRISI TerrSet software from Clark Labs. In a first step, a transition probability matrix for the period 1986–2001 was computed using Markov chains with the LULC map of 1986 as the first land cover image and the map of 2001 as the last. The Markov transition areas, together with the transition suitability image collection created in the previous step were used in a Cellular Automata model to predict the LULC in 2017. A second transition probability matrix was calculated using the 2001 and 2017 LULC maps and used to predict LULC in 2033. Finally, we calculated a transition matrix for the entire period (1986–2017), used to predict the LULC in 2050. These transition probabilities matrices contain the probability that each land cover category will change to any other (Eastman, 2016; Wang et al., 2016).

During the Markov chain model setting stage, the number of time periods to forward projection was set accordingly the number of time periods between the first and the second image for each period analyzed. In the Cellular Automata/Markov Change prediction setting, the later land cover image used in the Markov Chain analysis was used as the starting point for change simulation. A standard 5 * 5 contiguity filter was applied meanwhile the number of Cellular Automata iterations depended on the number of time periods for forward projection specified in the Markov chain analysis (Takada et al., 2010; Wang et al., 2018).

To evaluate the predictive performance of the model, we first compared the 2017 resulting simulation with the 2017 LULC map, using Kappa variations (Pontius, 2000): Kappa standard (Kstandard), Kappa for no information (Kno), and Kappa for location (Klocation). For all of the Kappa statistics, 0% indicates that the level of agreement is equal to the agreement due to chance and 100% indicates perfect agreement. In comparing the map of reality to the alternative map, Kno indicates the overall agreement. Klocation indicates the extent to which the two maps agree in terms of location for each category (Eastman, 2016). We accepted the model to make future projections only if the Kappa values were greater than 80% (Araya and Cabral, 2010).

3.3. Carbon storage

Although a national aboveground biomass map at a high resolution have been produced for Mexico (Cartus et al., 2014) providing detailed and spatially explicit estimates of aboveground biomass density to assist natural resource management (Rodríguez-Veiga et al., 2016), these forest aboveground carbon stocks were produced for the year 2005 and only consider aboveground biomass values. Considering this, we used the Carbon Storage and Sequestration model within the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) software developed by the Natural Capital Project (Sharp et al., 2015) to determine the existing carbon stocks using four carbon pools (aboveground biomass, underground biomass, dead organic matter and soil carbon) (Zhang et al., 2017; Pechanec et al., 2018). InVEST 3.4.2 for windows is a suite of free and open source software models used to map and assess goods and services provided by nature (Sharp et al., 2015; Sun et al., 2018). InVEST is a geospatial modeling framework that uses LULC maps as information sources and produces raster maps as outputs (Sallustio et al., 2015). In this study, the land use and land cover maps generated in the previous steps were used as input maps, whereas the carbon coefficients for all four carbon pools were derived from values reported in scientific literature for localities in several regions in Mexico with similar conditions to those of the study area (Ordóñez et al., 2008; Jaramillo et al., 2003; Adame et al., 2013, 2015).

4. Results

The confusion matrix was constructed based on 581 reference points (272 extracted from SPOT 7 image and 309 from the field campaigns). The accuracy indices for the 2017 thematic map are shown in Table 1. According to our results, this thematic map reached an overall accuracy of 83% and a Kappa coefficient of 0.76, statistically proving that the output classification was better than one produced by chance and it is representative of the study area landscape. Individually, the classes with the highest values for producer accuracy (PA) were AS, LI, SM, and MN with PA ≥ 90% each, whereas CR and ES had the lowest value, with PA of 63% and 75%, respectively (Table 1). Regarding the user's accuracies (UA), excluding the TDF (UA = 75%) and ES (UA = 74%) classes, all UA were above 80%. Because no ancillary data were available to validate the 1986 and 2001 maps, we assume an error level similar to that obtained for the 2017 classification because the procedure was the same.

Table 1
Accuracy assessment for an unsupervised classification of a Landsat OLI scene (2017). LI (Littoral), AS (Aquatic surfaces), EF (Evergreen Forest), TDF (Tropical Dry Forest), ES (Exposed soil), CR (Crops), SM (Saltmarsh), MN (Mangrove). UA = User´s accuracy, PA = Producer´s accuracy.

Classified data	Reference data								Sum	UA
	LI	AS	EF	TDF	ES	CR	SM	MN		
LI	**19**	0	0	0	0	0	0	0	19	100
AS	1	**10**	0	0	0	0	1	0	12	83
EF	0	0	**194**	20	5	0	0	1	220	88
TDF	0	0	30	**144**	17	0	0	1	192	75
ES	0	0	9	4	**67**	11	0	0	91	74
CR	0	0	0	1	0	**19**	0	0	20	95
SM	0	0	0	0	0	0	**9**	0	9	100
MN	0	0	0	0	0	0	0	**18**	18	100
Sum	*20*	*10*	*233*	*169*	*89*	*30*	*10*	*20*	***581***	
PA	95	100	83	85	75	63	90	90		

Overall accuracy = 83%; Kappa coefficient: 0.76.

4.1. Landscape change

The LULC change analysis covered approximately 13,020 km^2. LULC maps for 1986, 2001 and 2017 are shown in Fig. 2 while simulated maps are shown in Fig. 3. The area estimated for each classified and projected LULC classes is in Table 2. Along the study period, the presence of natural covers (principally EF and TDF) mainly characterized the study area, that together amounted around 85% of the total area in 1986, diminishing to just above 76% in 2017. From this, EF (mostly located on high elevations and irregular topography, dominated by pines and oaks) was the dominant LULC class, occupying above 40% of the total area in all dates.

The most important change from 1986 to 2001 was an increase of about 61,000 ha of the ES class (mainly dedicated to induced/cultivated grassland) that could be considered the main driver of land transformation. By contrast, EF and TDF classes showed a decrease in their extent by 32,200 ha and 40,000 ha, respectively. Even with this reduction in their extent (about 5%), both classes account 79% of the study area in 2001. The main changes for the period 2001–2017 were related to the same three categories, with EF and TDF losing 25,000 ha and 7,200 ha respectively; whereas ES increased by 26,800 ha its extent. Finally, the main landscape modifier for the entire analyzed period (1986–2017) was the ES class that increased from 10% (133,600 ha) in 1986–17% (221,500 ha) in 2017, a net gain of 87,900 ha.

Although coastal wetlands (littoral, mangrove, saltmarsh and aquatic surfaces) as a whole apparently remained unchanged, individually were the most dynamic classes. The conversion from one class to the other does not follow a monotonic pattern as in EF, TDF, and ES, so no trends were detected. Even when the HS class increased its extent in the period analyzed, it occupied only a small portion of the study area (less than 1%).

The change detection matrices for the periods 1986–2001, 2001–2017, and 1986–2017, allow us the interperiod comparison (Table 3). In all cases, the ES class mostly increased its extent at expenses of the EF and TDF classes; meanwhile, the area lost in this class seems to be a consequence of an increase of the cultivated lands (CR class). Saltmarsh class was identified as the main contributor to aquatic surfaces class. Even when the accuracy assessment showed a high agreement between the observed in the field and the classified image; it is important to note that some discrepancies exist between the EF and the TDF classes. Overall figures identify the TDF growing up over the EF class (conversion of evergreen forest to tropical dry forest). This could be due to reasons such as the phenologic characteristics of the vegetation, with both coverages inducing to spectral confusion during the image classification. As expected, all categories contributed to the increase of human settlements class.

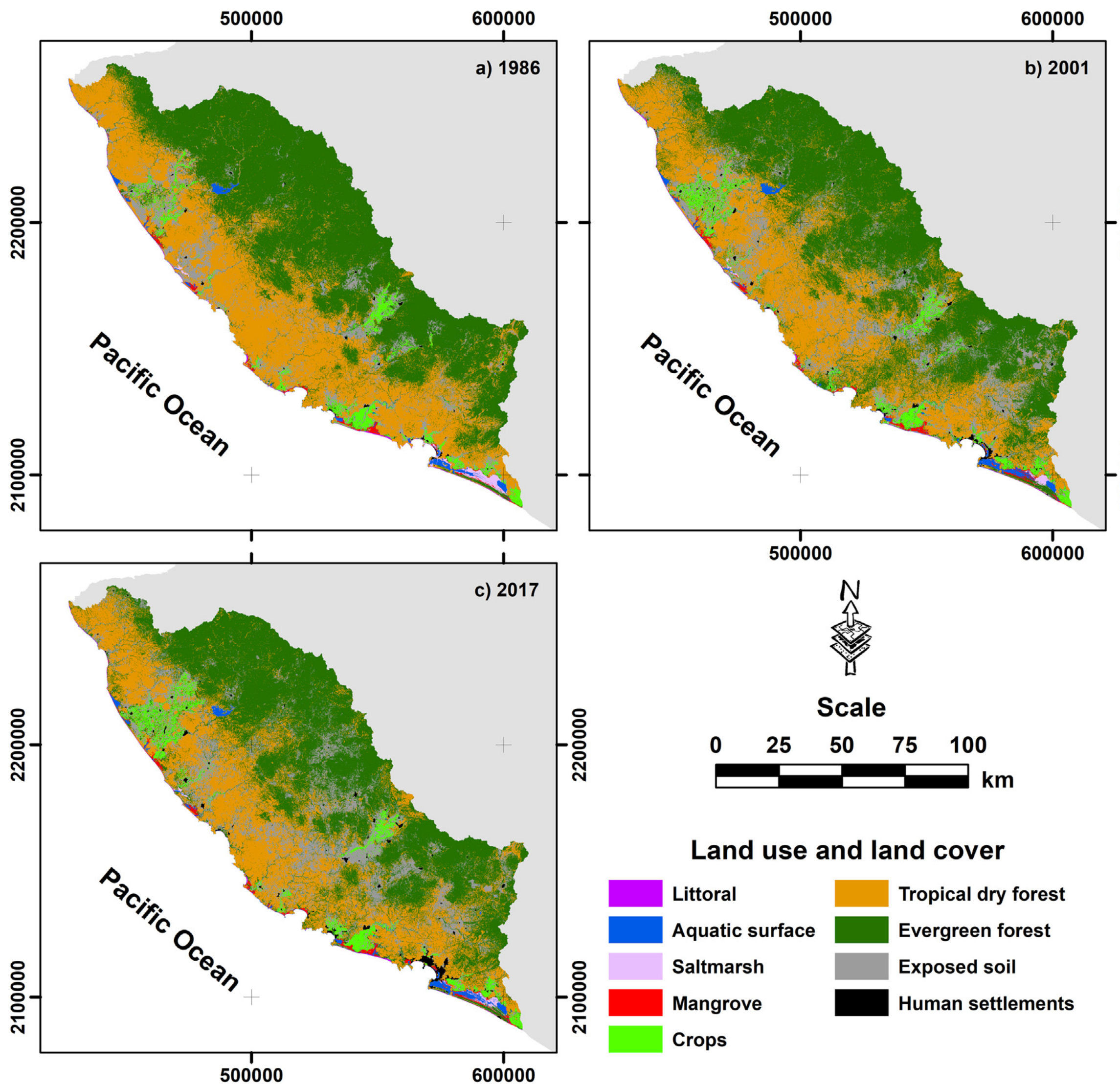

Fig. 2. Land use and land cover time-series for the hydrologic basin RH15 – Costa de Jalisco from un-supervised classification of Landsat TM, ETM+, and OLI imagery (1986, 2001, and 2017).

4.2. CA-Markov validation and scenario modeling

The land use and land cover transition probabilities for 1981–2001, 2001–2017, and 1986–2017 periods are shown in Table 4. In all cases, the ES class was the most susceptible to change to CR class; whereas the AS had a high probability of change to SM class.

Visual inspection of the modeling results (Figs. 2 and 3) shows that the simulated map for the year 2017 is reasonably similar to the 'real/classified' map for that year. Validation of CA-Markov was performed, and the accuracy test of the simulation model was considered acceptable with a Kappa coefficient of 0.82 between the classified and the projected LULC maps of 2017. A more detailed analysis was accomplished using the Kappa variations. The Kno, which also gives the overall accuracy of the simulation, is calculated to be 0.88. The model performed very well in the ability to specify location correctly (Klocation = 0.83).

Regarding this and assuming that trends of change will be similar to the evaluated for previous dates, the projected land use and land cover changes by 2033 yielded subtle but measurable changes mainly in the EF class, predicting a reduction in its extent by 15,900 ha and an increase of about 14,100 ha of the ES class (Table 2). Finally, from 2017 to 2050 the main expected changes are a reduction of the EF (42,200 ha) and the TDF (26,200 ha) with an imminent increase of about 44,900 ha and 16,200 ha in the ES and CR classes, respectively.

4.3. Carbon storage

Results obtained with the InVEST model revealed that conversion of natural vegetation covers (EF and TDF) into human-induced LULC classes resulted in a decrease of the carbon storage in the study area. The total carbon stock estimated for natural vegetation present in the study area in 1986 amounted 363 TgC, being reduced to 336 TgC in 2017, which represent a loss around 0.9 TgC per year. If current trends detected continue unchanged, a net loss of 45 TgC by the year 2050 could be expected. However, based in the projected LULC maps, a slight reduction in the deforestation rates after 2017 would produce a reduction in the carbon stock loss up to 0.7 TgC per year, representing 12% of the carbon stock in 1986 (Table 5). Based on the presented results, the largest contribution came from aboveground biomass (42%), followed by carbon stored in soil (41%), belowground biomass (10%) and the C stored as litter (7%).

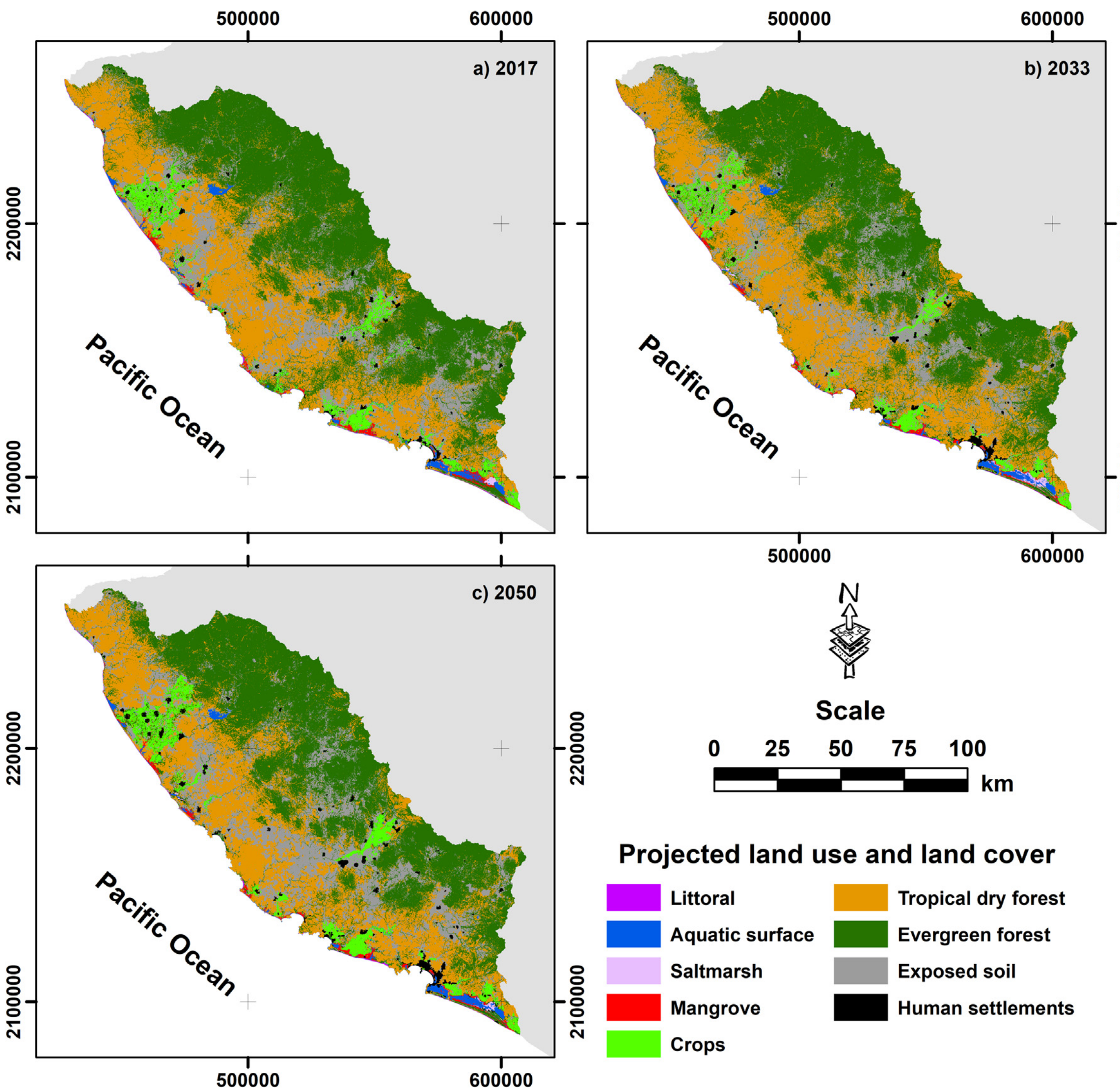

Fig. 3. Land use and land cover maps of the hydrologic basin RH15 – Costa de Jalisco for the period 2017–2050 projected using Cellular Automata-Markov model.

5. Discussion

Our results highlighted that the study area maintains a rural profile, with a low-density population, where less than 1% of the area corresponds to human settlements. Although the presence of natural covers (EF and TDF) characterized the study area, an increase in the

Table 2
Total estimated area (ha) by land use/cover classes in RH15 – Costa de Jalisco basin. Classified (1986–2001-2017) and Projected areas (2017–2033-2050). LI (Littoral), AS (Aquatic surfaces), EF (Evergreen Forest), TDF (Tropical Dry Forest), ES (Exposed soil), CR (Crops), SM (Saltmarsh), MN (Mangrove), HS (Human settlements).

	Date	Area	LULC Category								
			LI	AS	EF	TDF	ES	CR	SM	MN	HS
Classified maps	1986	ha	2502	10353	635622	468382	133593	36194	6946	5644	2662
		%	0.2	0.8	48.8	36.0	10.3	2.8	0.5	0.4	0.2
	2001	ha	2209	12240	603356	428366	194674	44141	2667	8323	5922
		%	0.2	0.9	46.3	32.9	15.0	3.4	0.2	0.6	0.5
	2017	ha	2174	12468	578387	421176	221493	45531	3089	7295	10284
		%	0.2	1.0	44.4	32.4	17.0	3.5	0.2	0.6	0.8
Change in area since 1986 (ha)			-328	2115	-57235	-47206	87901	9337	-3857	1652	7622
Projected maps	2017	ha	2017	12829	576858	403844	231601	55315	1088	9331	9015
		%	0.2	1.0	44.3	31.0	17.8	4.2	0.1	0.7	0.7
	2033	ha	1954	12526	562458	417602	235618	47881	3297	6589	13973
		%	0.2	1.0	43.2	32.1	18.1	3.7	0.3	0.5	1.1
	2050	ha	1856	13300	536149	394967	266416	61746	1309	7483	18672
		%	0.1	1.0	41.2	30.3	20.5	4.7	0.1	0.6	1.4
Expected change since 2017 (ha)			-317	832	-42238	-26208	44923	16214	-1780	187	8387

Table 3
Transition matrices for the LULC (ha) of the RH15 Costa de Jalisco basin for the period 1986–2017. LI (Littoral), AS (Aquatic surfaces), EF (Evergreen Forest), TDF (Tropical Dry Forest), ES (Exposed soil), CR (Crops), SM (Saltmarsh), MN (Mangrove), HS (Human settlements). The values in the diagonal represents the areas that remained unchanged between both dates, whereas the off-diagonal values indicate the intensity and direction of the change between the different LULC analyzed.

Category		1986									Total (ha)
		LI	AS	EF	TDF	ES	CR	SM	MN	HS	
2001	LI	**1568**	195	29	131	241	18	6	20	1	2209
	AS	313	**9214**	161	379	239	127	1660	146	0	12240
	EF	46	198	**514141**	66762	15368	5199	1237	393	12	603356
	TDF	63	79	81366	**326548**	19174	951	68	113	4	428366
	ES	368	290	33628	68781	**82728**	8312	422	116	28	194674
	CR	76	94	4960	4318	13594	**20574**	78	444	4	44141
	SM	1	17	9	60	258	21	**2275**	26	0	2667
	MN	8	227	1089	748	339	659	909	**4346**	0	8323
	HS	58	39	240	655	1652	333	291	40	**2613**	5922
Total (ha)		2502	10353	635622	468382	133593	36194	6946	5644	2662	**1301897**
Overall Kappa: 0.82											
Category		2001									Total (ha)
		LI	AS	EF	TDF	ES	CR	SM	MN	HS	
2017	LI	**1484**	222	18	68	318	44	7	5	7	2174
	AS	184	**10351**	334	132	411	179	302	569	5	12468
	EF	90	244	**474900**	65206	30814	5840	174	1104	14	578387
	TDF	212	370	76234	**310743**	30593	2607	68	329	19	421176
	ES	186	342	44464	49103	**116666**	10356	236	104	37	221493
	CR	2	96	5786	2320	13038	**23654**	5	621	10	45531
	SM	0	268	369	16	97	16	**1821**	502	0	3089
	MN	19	308	807	253	203	608	53	**5041**	3	7295
	HS	30	39	443	525	2534	836	2	48	**5828**	10284
Total (ha)		2209	12240	603356	428366	194674	44141	2667	8323	5922	**1301897**
Overall Kappa: 0.82											
Category		1986									Total (ha)
		LI	AS	EF	TDF	ES	CR	SM	MN	HS	
2017	LI	**1643**	205	13	130	145	6	9	21	2	2174
	AS	305	**8678**	283	452	225	192	1983	349	1	12468
	EF	130	245	**497139**	57163	17725	4560	787	619	18	578387
	TDF	219	276	81462	**316415**	21137	1379	124	160	2	421176
	ES	97	409	49948	87251	**75024**	8333	322	100	9	221493
	CR	4	122	5222	4385	15658	**19833**	14	292	1	45531
	SM	0	63	11	36	93	5	**2837**	43	0	3089
	MN	21	273	929	701	471	511	417	**3973**	0	7295
	HS	83	82	614	1850	3114	1375	453	87	**2628**	10284
Total (ha)		2502	10353	635622	468382	133593	36194	6946	5644	2662	**1301897**
Overall Kappa: 0.81											

agriculture-related classes (pasture and crops) was detected during the study period and it is expected to remain in the projected dates. These conversions not only reduce the natural covers but also increase the fragmentation in the region and, therefore an ecosystem C loss (Jaramillo et al., 2003).

Given that LULC maps are the main inputs, it is necessary to make them trustworthy to have confidence for upcoming analyses based on them. The results obtained for the imagery classification were acceptable, as the accuracy evaluation output values represented high concordance between the classification and the reference data, which in agreement with the Landis and Koch (1977) categorization, corresponds to substantial to almost perfect agreement.

Although the conversion from one land use to another does not follow a similar pattern due to natural and anthropogenic factors, a general trend was observed with a constant loss of EF and TDF classes and the increasing of agricultural soils (crops and exposed soils) and HS during the period analyzed (1986–2017). This trend possibly continues to 2050, according to the Markovian approach used here to model future LULC change processes.

Markov chains modeling has been used to propose future changes in land use/land cover (López et al., 2001; Flamenco-Sandoval et al., 2007; Camacho-Valdez et al., 2016), based in previously estimated trends. Besides their utility in exploratory analysis and for depicting contrasting scenarios, the projected LULC patterns are based in the current transition probabilities, and do not involve drivers of change (Berlanga-Robes and Ruiz-Luna, 2011). To support the reliability of the Markov's chains approach in the study area, we evaluated the predictive power of the model by comparing the simulation model with the reference map for the year 2017, obtaining results of the evaluated indices, all above than those considered by several authors as valid and with a high degree of consistency (Kamusoko et al., 2009; Liang et al., 2017; Mosammam et al., 2017; Wang et al., 2018). The LULC change projection reached values corresponding to an almost perfect agreement (0.81 ≤ Kappa ≤ 0.99), in accordance with Landis and Koch (1977), and Viera and Garrett (2005).

Although our models were generated with a sufficiently high degree of consistency to be useful and could be considered better than the results obtained by chance, our results should be considered with caution. One of the main constrains for the present study is the simplified carbon cycle provided by the InVEST model. This model assumes that LULC types are not gaining or losing carbon over time (Powers and Leighton, 2014; Sun et al., 2018), and the only changes in carbon storage are due to LULC changes (Pechanec et al., 2018). In addition, the model does not to take into account that some areas are undergoing natural succession, with variations in the carbon storage rates, which are constant for each LULC, even when significant variation could be observed by land cover type, depending on environmental conditions. In agreement with Dai et al. (2014, 2015) and Verduzco et al. (2015), the rainfall is the main determinant for carbon fixation in the TDF, as biomass growth depends on it, but also warming could seriously impact carbon storage in the tropical dry forest, reducing significantly its ability for carbon storage.

Table 4
Transitional probabilities matrices for LULC (ha) of the RH15 Costa de Jalisco basin for the period 1986–2017. LI (Littoral), AS (Aquatic surfaces), EF (Evergreen Forest), TDF (Tropical Dry Forest), ES (Exposed soil), CR (Crops), SM (Saltmarsh), MN (Mangrove), HS (Human settlements). In these matrices, rows represent the older land cover categories and the columns represent the newer categories; the values in the diagonal represents the probability of a LULC class remaining the same, that is, the resistance to change from one LULC class to another, whereas the off-diagonal values indicate the probabilities of change from one class to another.

1986–2001									
Category	LI	AS	EF	TDF	ES	CR	SM	MN	HS
LI	**0.5784**	0.1437	0.0150	0.0253	0.1740	0.0345	0.0006	0.0027	0.0258
AS	0.0216	**0.8813**	0.0198	0.0072	0.0306	0.0093	0.0020	0.0243	0.0039
EF	0.0000	0.0002	**0.7866**	0.1460	0.0574	0.0075	0.0000	0.0018	0.0003
TDF	0.0003	0.0008	0.1602	**0.6551**	0.1720	0.0087	0.0002	0.0016	0.0012
ES	0.0021	0.0019	0.1271	0.1661	**0.5622**	0.1220	0.0023	0.0026	0.0137
CR	0.0005	0.0038	0.1623	0.0226	0.2738	**0.5050**	0.0007	0.0213	0.0099
SM	0.0006	0.2811	0.2074	0.0085	0.0669	0.0129	**0.2186**	0.1556	0.0484
MN	0.0041	0.0285	0.0752	0.0193	0.0194	0.0925	0.0054	**0.7479**	0.0075
HS	0.0004	0.0000	0.0045	0.0014	0.0117	0.0015	0.0000	0.0000	**0.9804**
2001–2017									
Category	LI	AS	EF	TDF	ES	CR	SM	MN	HS
LI	**0.6717**	0.0835	0.0409	0.0959	0.0844	0.0011	0.0002	0.0088	0.0136
AS	0.0181	**0.8457**	0.0199	0.0303	0.0279	0.0078	0.0219	0.0252	0.0032
EF	0.0000	0.0006	**0.7871**	0.1264	0.0737	0.0096	0.0006	0.0013	0.0007
TDF	0.0002	0.0003	0.1522	**0.7254**	0.1146	0.0054	0.0000	0.0006	0.0012
ES	0.0016	0.0021	0.1583	0.1571	**0.5993**	0.0670	0.0005	0.0010	0.0130
CR	0.0010	0.0041	0.1323	0.0591	0.2346	**0.5359**	0.0004	0.0138	0.0189
SM	0.0026	0.1131	0.0653	0.0253	0.0884	0.0017	**0.6830**	0.0200	0.0006
MN	0.0006	0.0684	0.1326	0.0395	0.0125	0.0746	0.0603	**0.6057**	0.0057
HS	0.0012	0.0008	0.0024	0.0032	0.0062	0.0016	0.0000	0.0005	**0.9841**
1986–2017									
Category	LI	AS	EF	TDF	ES	CR	SM	MN	HS
LI	**0.6151**	0.1404	0.0560	0.1007	0.0419	0.0000	0.0000	0.0090	0.0369
AS	0.0228	**0.8241**	0.0234	0.0281	0.0438	0.0126	0.0073	0.0300	0.0080
EF	0.0000	0.0004	**0.7560**	0.1464	0.0876	0.0073	0.0000	0.0015	0.0006
TDF	0.0003	0.0010	0.1362	**0.6296**	0.2187	0.0091	0.0001	0.0015	0.0035
ES	0.0013	0.0017	0.1498	0.1835	**0.4935**	0.1399	0.0008	0.0039	0.0256
CR	0.0001	0.0059	0.1422	0.0383	0.2725	**0.4816**	0.0002	0.0167	0.0424
SM	0.0007	0.3399	0.1316	0.0170	0.0508	0.0013	**0.3120**	0.0717	0.0751
MN	0.0041	0.0701	0.1238	0.0280	0.0162	0.0611	0.0092	**0.6713**	0.0164
HS	0.0007	0.0006	0.0075	0.0007	0.0038	0.0006	0.0000	0.0000	**0.9862**

Table 5
Total carbon stock by date (Tg C) in the hydrologic basin RH15 – Costa de Jalisco, Mexico.

Carbol pool	1986	2001	2017	2033	2050
Total carbon	362.91	347.98	336.23	328.97	317.92
Aboveground carbon	152.42	145.07	140.26	137.20	131.41
Belowground carbon	36.85	35.61	34.32	33.49	32.29
Soil carbon	147.72	142.93	137.64	134.47	131.36
Dead mass carbon	25.91	24.37	24.01	23.81	22.86

Neither of the above drivers is included in the applied modeling approach, increasing the uncertainty in the estimations, that only could be reduced through in situ evaluations to increase the accuracy and precision of estimates (Goulden et al., 1996). Also, under-estimation of carbon storage by human settlements must be regarded, as some evidences suggest that urban areas are important carbon reservoirs, mainly stored in green spaces and urban trees (Sallustio et al., 2015; Gratani et al., 2016), although there is a limited evidence supporting the carbon sequestration efficiency of urban vegetation (Velasco et al., 2016). In this study, we decided do not consider the carbon values in human settlements to provide a more conservative approach, as suggested by Sallustio et al. (2015). Considering this, our results clearly indicate a continuous decrease of natural vegetation covers (EF and TDF), and a subsequent increase in the human-induced LULC classes, which in agreement with the model could result in a decrease in the carbon storage in the study area, that must be considered for future management plans, modifying strategies to improve the carbon sequestration rates to compensate the loss attributable to LULC changes.

Despite the uncertainty of the measurements, this study provides with a first approximation to the carbon storage analysis in the study area and a baseline useful for LULC change assessments, related with the carbon cycle. This methodological approach combines remote sensing analysis and GIS modeling, easily applicable at a basin scale, solving in part the deficiency of local data for carbon storage estimation.

For future research, it will be necessary to obtain a better description of the gradient pattern of land covers, to obtain more accurate carbon storage values in these land covers during each time period, and to quantify gradient change in terrestrial carbon stocks in response to land use and cover change (Zhang et al., 2017). These problems can be addressed by dividing land use types into different successional classes (Sun et al., 2018).

The TDF is one of the most biodiverse ecosystems of the world, however, is also one of the most threatened, mainly due to anthropogenic fragmentation. Because of the attractive climatic and edaphic characteristics of the TDF, large human populations have been historically settled in some regions (Janzen, 1988; Sánchez-Azofeifa et al., 2005; Portillo-Quintero et al., 2013), and associated with this, these forests have suffered intense transformations due to agriculture and livestock (as show this study). Our results showed that human settlements as such have not had great impact in landscape transformation in the study area, however, land transformation mainly for farmlands has had and will have a significant impact in both dry and evergreen forests. The conversion rates of the original forests clearly indicate that most of the mature forests will eventually disappear, and as a consequence, complex landscapes occupied by fragments of original vegetation and others under different successional stages contained within matrices of completely transformed habitat will remain (Quesada et al., 2009). Because of this, ecologic and genetic studies at landscape level are necessary to know which biotic and abiotic factors as well as which selective forces have and could shaped and maintain diverse life forms in these threatened ecosystems.

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Disclosure statement

The authors declare no conflict of interest.

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