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Changes in land uses and vegetation cover in forests with restoration history in Durango, Mexico

Cambios en los usos del suelo y cobertura vegetal en bosques con historial de restauración en Durango, México

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ABSTRACT

An effective way to understand the dynamics of forest ecosystems is by quantifying changes in land use and vegetation cover. The objective of this study was to carry out a multi-temporal analysis in areas with a history of soil conservation and restoration activities within the Santiago River sub-basin, located in the Upper Nazas River Basin, Durango. Satellite images from the years 1999, 2005, 2011, 2017, and 2023 were analyzed using a supervised classification with 10 land use and vegetation classes. Based on this classification, change rates were calculated, and permanence/transition matrices were generated for each class. Additionally, the Normalized Difference Vegetation Index (*NDVI*) and the Normalized Difference Moisture Index (*NDMI*) were calculated for 11 forests properties. Throughout all years analyzed, pine forest showed the greatest coverage, with a recovery of 1,898 hectares in 2023 at an annual rate of 0.19%. In contrast, the highest degradation was observed in pine-oak and oak forests. Pine forest also exhibited the greatest permanence before and after 2011. The highest *NDVI* value was recorded in 2023, while the *NDMI* was negative across all forest properties. Although reforestation initiatives have contributed to the increase in pine forest cover, the region continues to be affected by timber harvesting and periods of drought.

Keywords: changes matrix, multitemporal analysis, rate change, vegetation indices.

RESUMEN

Una forma eficaz de comprender la dinámica de los ecosistemas forestales es mediante la cuantificación de los cambios en el uso del suelo y la cobertura vegetal. El objetivo de este estudio fue realizar un análisis multitemporal en áreas con antecedentes de obras de conservación y restauración de suelos dentro de la subcuenca del Río Santiago, ubicada en la Cuenca Alta del Río Nazas, Durango. Se analizaron imágenes correspondientes a los años 1999, 2005, 2011, 2017 y 2023, utilizando una clasificación supervisada con 10 clases de uso del suelo y vegetación. A partir de estas, se calcularon las tasas de cambio y se generaron matrices de permanencia/transición para cada clase. Adicionalmente, se calcularon el Índice de Vegetación de Diferencia Normalizada (*NDVI*) y el Índice de Humedad de Diferencia Normalizada (*NDMI*) para 11 predios forestales. En todos los años, el bosque de pino presentó la mayor cobertura, con una recuperación de 1.898 hectáreas en 2023 a una tasa anual de 0,19%. En contraste, la mayor degradación se registró en los bosques de pino-encino y encino. El bosque de pino también presentó la mayor permanencia antes y después del 2011. El valor más alto de *NDVI* se registró en 2023, mientras que el *NDMI* fue negativo en todos los predios forestales. Si bien las iniciativas de reforestación han contribuido al aumento de la cobertura de los bosques de pino, aún persisten impactos asociados al aprovechamiento maderable y a los períodos de sequía que han afectado a la región.

Palabras clave: matriz de cambios, análisis multitemporal, tasa de cambio, índices de vegetación.

INTRODUCTION

Throughout history, terrestrial ecosystems have continually changed due to natural and anthropogenic factors. These activities have resulted in shifts in land use and vegetation cover, which are linked to the production of goods and services that contribute to human well-being. Over the past four decades, there has been a net loss of 178 million hectares (ha) of forests worldwide. Currently, the total forest area stands at 4,060 million ha, accounting for 31% of the planet's total land area (FAO, 2020).

In Mexico, the decline in vegetation cover mirrors global trends. Temperate forests cover approximately 20% of the national territory, yet they have significantly decreased in both area and diversity of species, with an average annual deforestation rate exceeding 0.5% (Galicia et al., 2015). For instance, Mexico's watersheds lost between 1% and 20% of their natural vegetation from 1976 to 2009 (Cuevas et al., 2010). Specifically, the vegetation cover in the upper part of the Nazas River basin, a hydrological region of great economic, ecological, and social importance in Durango, has faced intense productive activities, particularly in forestry, mining, and agriculture. These activities have led to severe environmental impacts, including vegetation loss and soil erosion (Torres-Aguayo, 2012).

In response to these impacts, several projects have been initiated to reverse or mitigate environmental degradation. These include efforts by ejidos and forest communities, the Payment for Hydrological Environmental Services Program (PSAH), and the Laguna Metropolitan Fund. The first two initiatives have been promoted by the National Forestry Commission (CONAFOR) since 2011. Implemented actions include reforestation and practices to control soil erosion (Aguirre-Calderón et al., 2015).

One effective method for understanding the dynamics of forest ecosystems is through quantifying changes in soil and vegetation cover. This analysis can reveal rates of deforestation or increases in forest cover over time and helps determine their geographic extent (Barrero-Medel et al., 2022). Local-level change analysis provides accurate and timely information on these changes, even identifying which productive activities have the greatest impact (Bonilla-Moheno et al., 2012). Satellite remote sensing is a valuable technology for this purpose, as it enables the analysis of large areas with high temporal frequency. This technology incorporates sensors like the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), facilitating the extraction of key phenological parameters and monitoring vegetation dynamics through multitemporal analysis (Dindaroglu et al., 2021).

Several studies in different regions of Mexico have evaluated changes in land use and vegetation through multitemporal analyses (Sandoval-García et al., 2021; Hernández-Cavazos et al., 2023; Pimienta-Ramírez et al., 2025). However, few have focused on the impact of soil conservation and restoration efforts. Given this context, the objective of this research was to conduct a multitemporal analysis in areas with a history of soil conservation and restoration efforts within the Santiago River sub-basin, part of the Upper Nazas River Basin in Durango. Using 2011 as a reference point, this study aims to identify an increase in forest area, a decrease in bare soil, and an improvement in vegetation indices.

METHODS

Study area. The research was conducted in the Santiago River sub-basin, which is located in the upper portion of the Nazas River basin in Durango, Mexico. This area covers 352,788 hectares. Geographically, it is situated between the parallels of 24° 01' 02'' and 25° 09' 79'' North latitude and meridians 104° 57' 20" and 105° 3' 16'' West longitude (Figure 1).

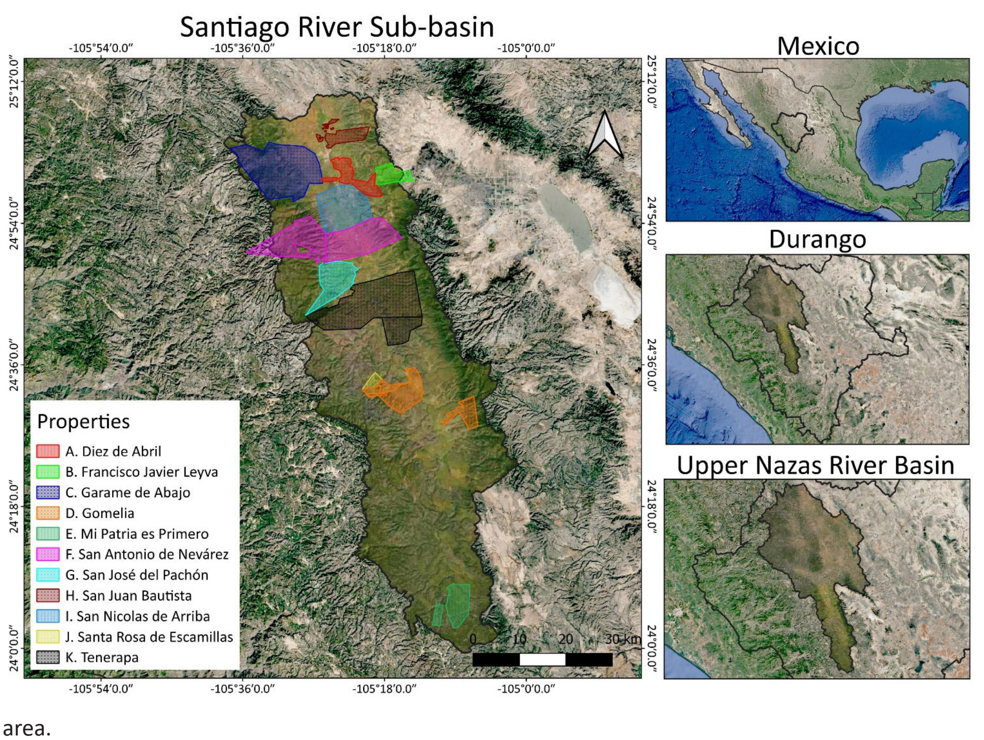

Figure 1. Study area.

Área de estudio.

The altitude above sea level in the area ranges from 1,700 to 3,000 m. The predominant soil types include lithosol, cambisol, and regosol, which generally have a coarse to medium texture. The climate is characterized as temperate sub-humid with summer rains, alongside semi-cold sub-humid conditions also featuring summer precipitation. The average annual precipitation is 1,200 mm, and the average temperature is 18 °C (INEGI, 2009).

In the study area, practices for conservation, restoration, and reforestation have been implemented since 2011, and these efforts have intensified particularly across 11 forest properties (Torres-Aguayo, 2012) (Figure 1, Table 1). These practices include the construction of filter dams, stone barriers along contour lines, protection of dead plant material, reforestation efforts, and actions aimed at preventing forest fires (Torres-Aguayo, 2012; Aguirre-Calderón et al., 2015).

Satellite image processing. Satellite image analysis was conducted using Google Earth Engine (GEE, 2025), a cloud-based computing platform that provides access to a comprehensive catalog of global datasets, including recent observations from multiple satellite missions. Landsat images of the study area were selected from the dry season to minimize cloud interference (< 5% cloud cover). This ensured clearer visibility of the landscape and its features, allowing for a more accurate analysis. The images were obtained from the United States Geological Survey (USGS, 2025) for the years 1999, 2005, 2011, 2017, and 2023 (Table 2).

The images included geometric, radiometric, and atmospheric corrections, which were processed to yield surface reflectance while ensuring maximum geometric accuracy (≤ 12 m). Each image was cropped to align with the boundaries of the study area. For Landsat 5, the selected bands were B1, B2, B3, B4, B5, B6, and B7, while the selected bands for Landsat 8 were B2, B3, B4, B5, B6, and B7, each with a spatial resolution of 30 m x 30 m (8 bits) (Table 3).

Furthermore, the relationships between bands were analyzed using normalization processes to create new combinations that enhance classification accuracy. For the images from 1999, 2005, and 2011, the combinations employed were B4-B5, B4-B7, and B5-B7. In contrast, for the images from 2017 and 2023, the combinations included B4-B5, B4-B6, B4-B7, B5-B6, B5-B7, and B6-B7. Afterward, the information was merged: a mosaic of 17 bands was generated for the years 1999, 2005, and 2011, while a mosaic of 16 bands was created for 2017 and 2023.

Supervised classification. For the classification process, a supervised approach was applied to each image segment. This method of pixel labeling involves the user selecting representative training data for each predefined class. High-resolution imagery from Google Earth was analyzed to visually identify land cover and land use types. Based on this analysis, ten classes were defined for the classification. To maintain consistency across the classification process, the presence of each land cover or land use class was verified at the same location in all images. The size, geometry (polygons, lines, and points), and number of samples of each class varied depending on the available pixels for each land use and vegetation type. Seventy percent of the samples for each class were utilized to train the algorithm, while the remaining 30% were used for validation (Pande et al., 2024) (Table 4).

Table 1. Area of the forest properties with history of soil conservation and restoration practices.

Superficie de los predios con antecedentes de obras de conservación y restauración de suelos.

Property	Area (ha)
A. Diez de Abril	3,844
B. Francisco Javier Leyva	2,044
C. Garame de Abajo	17,206
D. Gomelia	8,744
E. Mi Patria es Primero	4,878
F. San Antonio de Nevárez	17,810
G. San José del Pachón	6,086
H. San Juan Bautista de la Estancia	2,971
I. San Nicolás de Arriba	9,635
J. Santa Rosa de Escamillas	758
K. Tenerapa	22,919

Table 2. Landsat satellite images used in the analysis.

Imágenes satelitales Landsat utilizadas en el análisis.

Date	Satellite	Image (ID)
March 14, 1999	Landsat 5	LANDSAT/LT05/C02/T1_L2/LT05_031043_19990314
March 30, 2005	Landsat 5	LANDSAT/LT05/C02/T1_L2/LT05_031043_20050330
March 31, 2011	Landsat 5	LANDSAT/LT05/C02/T1_L2/LT05_031043_20110331
March 31, 2017	Landsat 8	LANDSAT/LC08/C02/T1_L2/LC08_031043_20170331
March 16, 2023	Landsat 8	LANDSAT/LC08/C02/T1_L2/LC08_031043_20230316

Table 3. Characteristics of the spectral bands of satellite images.

Características de las bandas espectrales de las imágenes satelitales.

Band	Landsat 5		Landsat 8	
	Electromagnetic spectrum	Wavelength (µm)	Electromagnetic spectrum	Wavelength (µm)
B1	Blue	0.450-0.515	Coastal sprays	0.435-0.451
B2	Green	0.525-0.605	Blue	0.452-0.512
B3	Red	0.630-0.690	Green	0.533-0.590
B4	Near Infrared (NIR)	0.755-0.900	Red	0.636-0.673
B5	Far Infrared (SWIR 1)	1.550-1.750	Near Infrared (NIR)	0.851-0.879
B6	Thermal Far Infrared (TIR)	10.400-12.500	Shortwave infrared 1 (SWIR 1)	1.566-1.651
B7	Thermal Near (SWIR 2)	2.090-2.350	Shortwave infrared 2 (SWIR 2)	2.107-2.294
B8	-	-	Panchromatic	0.50-0.68
B9	-	-	Cirrus	1.36-1.38
B10	-	-	Thermal Infrared (TIR) 1	10.60-11.59
B11	-	-	Thermal Infrared (TIR) 2	11.50-12.51

Table 4. Number of samples used for each land use and vegetation class.

Número de muestras utilizadas para cada clase de uso de suelo y vegetación.

Class	Training samples	Validation samples
1. Agriculture	82	35
2. Human settlements	61	26
3. Oak forest	48	21
4. Oak-pine forest	49	21
5. Pine forest	123	53
6. Pine-oak forest	56	24
7. Shrubbery	36	15
8. Grassland	89	38
9. Water bodies	11	5
10. Bare soil	183	79

Classification was conducted using the Random Forest algorithm, which is well-suited for land cover classification using medium- and high-resolution satellite data. This algorithm functions as an ensemble classifier, generating multiple decision trees based on random subsets of samples and training variables. One of its key advantages is its high classification accuracy (Belgiu & Drăgut, 2016). A training mesh with the selected samples for classification was applied to the images from each year, resulting in a raster that contains information about the defined classes.

To assess the accuracy of the classification, both overall accuracy and Kappa indices were calculated. Overall accuracy ranges from 0 to 1, with values closer to 1 indicating higher accuracy. Kappa values measure agreement with the field data, and the accuracy classification is as follows: < 0.00 (no agreement); 0.00-0.20 (fair); 0.21-0.40 (low); 0.41-0.60 (moderate); 0.61-0.80 (substantial); and 0.81-1.00 (near perfect) (Landis & Koch, 1977).

Determination of cover gains and losses. For the periods 1999-2005, 2005-2011, 2011-2017, and 2017-2023, as well as 1999-2011 and 2011-2023, the gains and losses in cover for the different classes were determined by calculating the annual rate of change using equation [1] (Palacio-Prieto et al., 2004).

$$\delta_n = \left(\left[\frac{S_2}{S_1} \right]^{\frac{1}{n}} - 1 \right) * 100 \qquad [1]$$

where: *δn* = rate of change expressed as percentage, *S1* = area at date 1, *S2* = area at date 2 and *n* = number of years in the period.

Land use and vegetation change matrix. To assess the permanence and exchange between land use classes, change matrices were created for the periods 1999-2011 and 2011-2023. This process involved overlaying the resulting land use and vegetation images and constructing two-dimensional tables following the methodology described by Pontius et al. (2004). The matrices were developed using QGIS version 2.18.10, and the MOLUSCE tool, which calculates change probabilities based on historical data for specified time intervals.

Vegetation indices. For the 11 forest properties, we calculated the Normalized Difference Vegetation Index (*NDVI*) and the Normalized Difference Moisture Index (*NDMI*) on an annual basis. These indices provide valuable insights into vegetation characteristics and help to understand ecosystem functioning.

NDVI ranges from -1 to 1. High values indicate significant photosynthetic activity in the vegetation cover and a strong relationship with evapotranspiration. Conversely, low values suggest little or no vegetation cover and reduced photosynthetic activity (Rouse et al., 1974). It was calculated using the following equation [2]:

$$NDVI = \frac{NIR - R}{NIR + R} \quad [2]$$

where *NIR* = Near Infrared Spectrum and *R* = Red Spectrum.

NDMI takes values between -1 and 1; it is used in a complementary way to *NDVI*, but they are mainly related to moisture content in plant tissues (Jin & Sader, 2005) (equation [3]).

$$NDMI = \frac{NIR - SWIR1}{NIR + SWIR1} \quad [3]$$

where *NIR* = Near Infrared Spectrum and *SWIR* 1 = Far Infrared.

RESULTS

Surface classification. Figure 2 illustrates the land use and vegetation classification in the Santiago River sub-basin for the years 1999, 2005, 2011, 2017, and 2023. The overall accuracy of the supervised classification of the satellite images averaged 0.81, with a Kappa coefficient averaging 0.77.

Land use and vegetation cover. Each land use and vegetation cover class had a distinct surface area that varied each year. Overall, the pine forest was the most widespread area, followed by grassland, pine-oak forest, and oak-pine forest. In 1999, the pine forest covered 78,700 ha (22.31%). By 2005, its area decreased to 74,677 ha (21.17%), but by 2011, it had increased to 80,901 ha (22.93%). By 2023, the area further expanded to 82,799 ha (23.47%). In 1999, grassland covered 76,181 ha (21.60%), but by 2005, this area declined to 66,353 ha (18.81%). However, from 2005 onward, the grassland area began to increase, reaching 78,248 ha (20.79%) by 2023. The oak-pine forest recorded an area of 38,771 ha (10.99%) in 1999, which increased to 49,158 ha (13.93%) by 2011. This area remained relatively stable, covering 49,972 ha (14.16%) in 2023. Conversely, the pine-oak forest, which

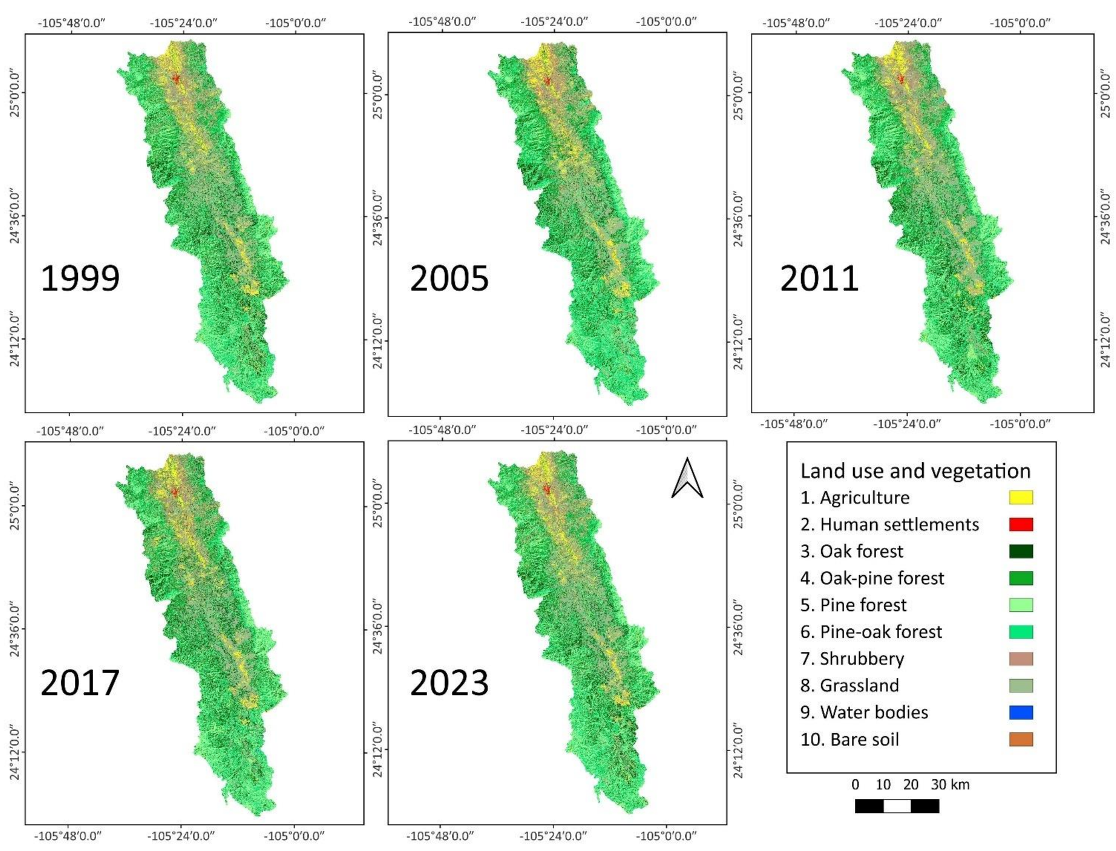

Figure 2. Land use and vegetation for the years 1999, 2005, 2011, 2017 and 2023.

Uso del suelo y vegetación para los años 1999, 2005, 2011, 2017 y 2023.

covered 80,131 ha (22.71%) in 1999, showed a downward trend. By 2011, its area declined to 70,785 ha (20.06%), and in 2023, it occupied only 63,563 ha (18.02%).

Although oak forests and shrublands represent a smaller portion of the total area, their importance in the classification is significant. In 1999, oak forests covered 11.69% of the area, but this percentage showed a downward trend, declining to 11.03% in 2011. However, by 2023, the area increased slightly to 11.29%. In contrast, scrublands accounted for 5.70% of the area in 1999. This coverage rose to 6.74% in 2017 but then decreased to 5.64% in 2023. The other land classes were smaller in area and had stable coverage throughout the years analyzed (Figure 3, Table 5).

Figure 4 shows the proportions of land use and vegetation across the 11 evaluated forest properties, confirming that all classes considered in the study were present in each of them. Overall, forest types (oak, oak-pine, pine, and pine-oak) dominated properties C, D, E, F, G, and J, comprising more than 50% of the total area in all years analyzed. The proportion of each forest type varied by year. Notably, pine forests were most prevalent on property E, accounting for 53% of the total area in 1999. This proportion decreased to 48% in 2011 but increased to 61% by 2023. On the other hand, shrubland and grassland were more prominent in properties A, B, H, I, and K, where they collectively represented over 40% of the area until 2017. By 2023, property K increased its area dedicated to these land types to 45%. While all properties included agricultural land, properties H and I consistently had the highest proportions, with values close to or exceeding 20% in all analyzed years (Figure 4).

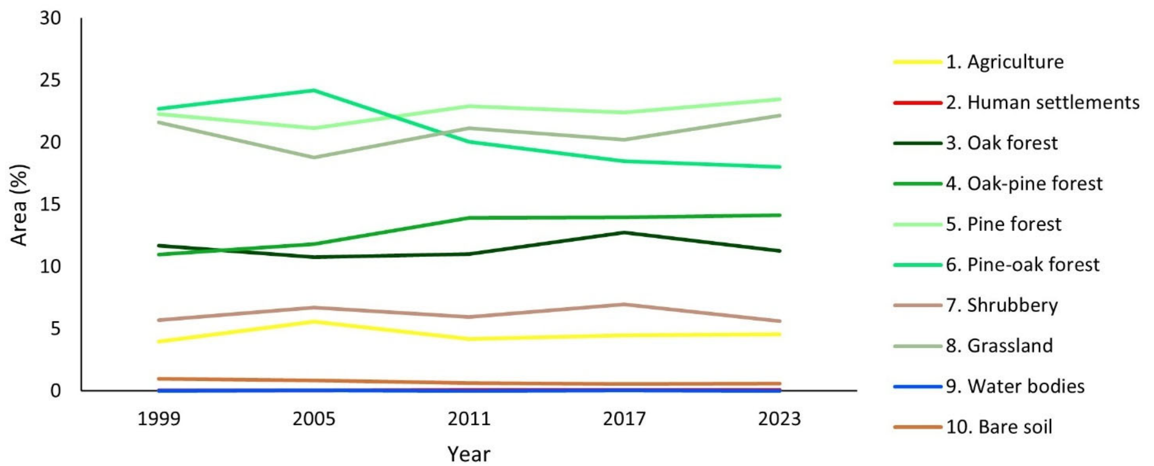

Figure 3. Percentage of land use and vegetation area for the years 1999, 2005, 2011, 2017 and 2023.

Porcentaje de superficie de uso de suelo y vegetación para los años 1999, 2005, 2011, 2017 y 2023.

Table 5. Surface area (ha) per year and annual rate of change per period (%) for each the land use and vegetation class.

Superficie (ha) por año y tasa anual de cambio por periodo (%) para cada una de las clases de uso de suelo y vegetación.

Class	Coverage (ha) per year					Annual rate of change per period (%)					
	1999	2005	2011	2017	2023	1999-2005	2005-2011	2011-2017	2017-2023	1999-2011	2011-2023
1	14,006	19,701	14,836	15,785	16,034	5.85	-4.62	1.04	0.26	0.48	0.65
2	210	217	262	283	305	0.57	3.2	1.27	1.27	1.88	1.27
3	41,257	37,988	38,913	44,993	39,828	-1.37	0.4	2.45	-2.01	-0.49	0.19
4	38,771	41,639	49,158	49,290	49,972	1.2	2.81	0.04	0.23	2	0.14
5	78,700	74,677	80,901	79,077	82,799	-0.87	1.34	-0.38	0.77	0.23	0.19
6	80,131	85,351	70,785	65,303	63,563	1.06	-3.07	-1.33	-0.45	-1.03	-0.89
7	20,103	23,707	20,970	24,579	19,894	2.79	-2.02	2.68	-3.46	0.35	-0.44
8	76,185	66,353	74,638	71,298	78,248	-2.28	1.98	-0.76	1.56	-0.17	0.39
9	32	142	38	135	63	28.13	-19.84	23.8	-11.98	1.35	4.39
10	3,392	3,014	2,286	2,046	2,083	-1.95	-4.5	-1.83	0.3	-3.23	-0.77

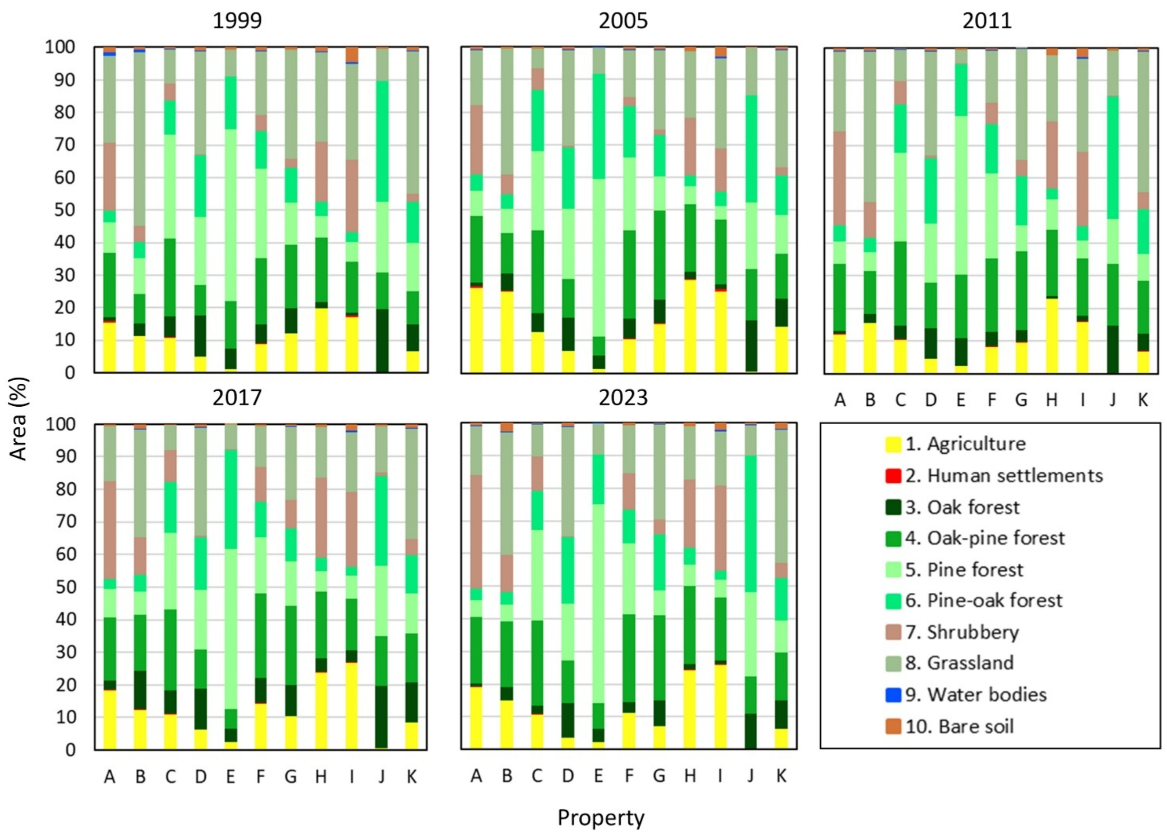

Figure 4. Percentage of land use and vegetation area per property for the years 1999, 2005, 2011, 2017 and 2023.

Porcentaje de superficie de uso del suelo y vegetación por predio para los años 1999, 2005, 2011, 2017 y 2023.

Changes in land use and vegetation cover. The annual rate of change varied across all classes, showing both increases and decreases in all time periods (Table 5). From 1999 to 2005, agriculture presented a rate of 5.85%, while grassland decreased by 2.28%, and oak forest declined by 1.37%. In the following period from 2005 to 2011, the trend shifted: agriculture fell by 4.62%, grassland increased by 1.98%, and oak forest showed a slight increase of 0.40%; however, the rate of change for the pine-oak forest was negative at -3.07%. From 2011 to 2017, the pine-oak forest's decline continued with a rate of -1.33%. Meanwhile, shrubland increased by 2.68%, and bare soil saw a decrease of 1.83%. In the period from 2017 to 2023, the pine-oak forest experienced a slight recovery with a rate of 0.45%, while the oak forest decreased by 2.01% and bare soil increased by 0.30%.

Looking at the period before restoration practices began (1999-2011), the oak and pine-oak forests had rates of change of -0.49% and -1.03%, respectively. In contrast, shrublands and pine forests showed positive rates of 0.35% and 2.00%. After the start of conservation practices (2011-2023), the oak and pine-oak forests recorded rates of 0.19% and -0.89%, respectively, while scrublands and pine forests showed rates of -0.44% and 0.19%. Human settlements exhibited positive rates across all periods (Table 5).

Matrix of changes in land use and vegetation. The transition matrix indicates the area (%) for each class that has been maintained as well as those that have changed to other classes. The values on the diagonal (*) refer to the area that has been maintained from one year to the next. From 1999 to 2011, 47% of the agricultural area remained stable, while 53% shifted to other classes, mostly to grassland (40%). Recovery was mainly observed from bare soil, accounting for 21%. In the case of oak forest, only 42% remained stable. While 58% changed to other land use and vegetation types, predominantly to oak-pine forest and pine-oak forest (25% and 17%, respectively). Although the oak forest recovered area, no class had a recovery greater than 12%.

For pine forest, 67% remained stable, with the remainder transforming mostly into pine-oak forest (19%). The recovery in this class mainly came from other areas of pine-oak forest (26%). Regarding bare soil, 22% remained, with transitions primarily occurring to grassland and agriculture at rates of 27% and 20%, respectively (Table 6).

The area dedicated to agriculture remained stable from 2011 to 2023, because 49% was converted to other classes, mainly grassland (34%), but there was a recovery of areas of bare soil (19%). The oak forest coverage stayed stable at 38%, with most transformations occurring towards pine-oak forest (21%). In addition, areas of oak-pine forest contributed to recovery, accounting for 18%. For pine forests, 66% remained stable, though there was a significant shift toward pine-oak forest (21%). The recovery in this area mostly came from other pine-oak forests (27%). In terms of bare soil, 33% was maintained, with a trend toward transitions to grassland and agriculture, which accounted for 23% and 19%, respectively (Table 7).

Vegetation indices. The average *NDVI* values per year showed similar trends across the 11 forest properties, increasing from 1999 to 2023. Properties E and J recorded the highest values, reaching a maximum of 0.17 and 0.159, respectively, in 2023. On the other hand, properties B and I registered the lowest values, with maximums of 0.12 and 0.13, respectively, in the same year. Overall, the *NDVI* value for all properties exhibited an upward trend, particularly between 2011 and 2023 (Figure 5A).

Throughout the study period, *NDMI* values remained negative for all forest properties. However, there was a consistent increase over time. Property C recorded the highest values in all years, ranging from -0.049 and -0.024; E reached its maximum value in 2023 (-0.035). Property B recorded the lowest values and the greatest variation, with *NDMI* va-

Table 6. Matrix of land use changes (%) in the period 1999-2011.
Matriz de cambios de uso de suelo (%) en el período 1999-2011.

	class	Coverage 2011 (%)									
		1	2	3	4	5	6	7	8	9	10
Coverage 1999 (%)	1	47*	4	0	0	0	0	7	40	0	2
	2	0	82*	0	0	0	0	0	4	0	14
	3	0	0	42*	25	5	17	1	10	0	0
	4	2	0	12	44*	10	22	6	4	0	0
	5	0	0	4	6	67*	19	1	3	0	0
	6	0	0	11	12	26	48*	1	2	0	0
	7	9	0	2	14	3	3	41*	26	0	2
	8	7	0	5	5	1	2	9	70*	0	1
	9	4	0	0	0	0	0	0	23	37*	36
	10	21	2	2	4	1	1	20	27	0	22*

*Area (%) that has been maintained from 1999 to 2011.

Table 7. Matrix of land use changes (%) in the period 2011-2023.
Matriz de cambios de uso de suelo (%) en el período 2011-2023.

	Class	Coverage 2023 (%)									
		1	2	3	4	5	6	7	8	9	10
Coverage 2011 (%)	1	51*	6	0	0	0	0	6	34	0	3
	2	2	71*	0	0	0	0	0	5	0	22
	3	0	0	38*	16	10	21	2	13	0	0
	4	0	0	18	42*	10	15	7	8	0	0
	5	0	0	4	6	66*	21	1	2	0	0
	6	0	0	11	16	27	42*	1	3	0	0
	7	5	0	3	16	3	1	43*	28	0	1
	8	9	0	6	4	2	1	5	72*	0	1
	9	5	0	0	3	0	1	1	30	43*	17
	10	19	4	5	3	2	2	8	23	1	33*

*Area (%) that has been maintained from 2011 to 2023.

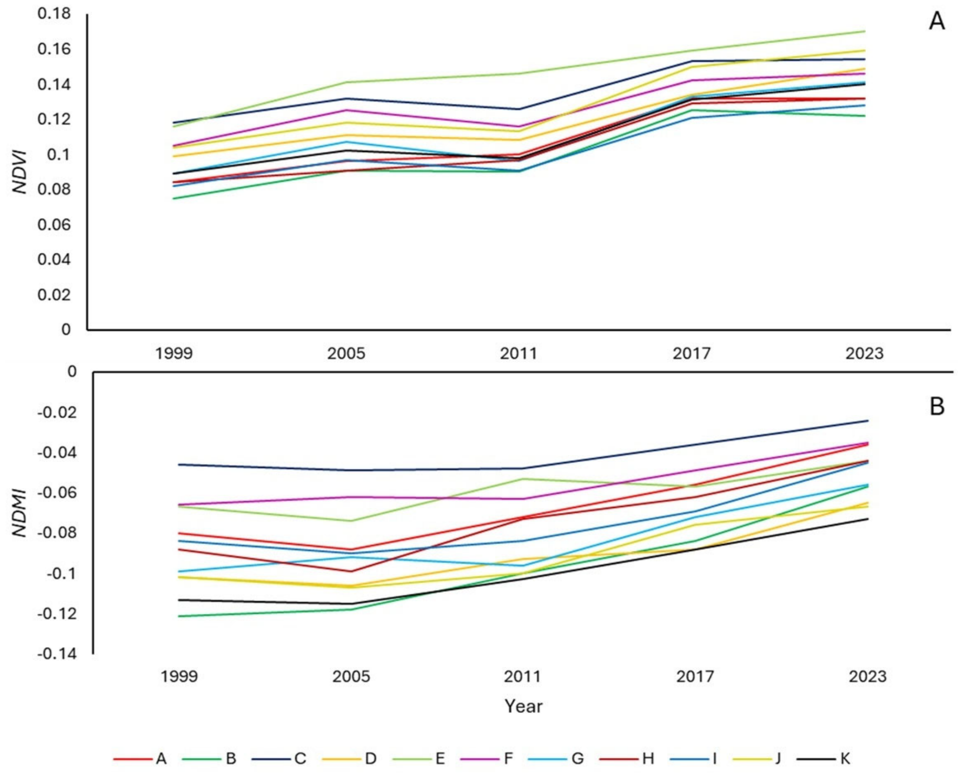

Figure 5. Yearly variation in average vegetation index values by forest property. Normalized Difference Vegetation Index (*NDVI*) (A). Normalized Difference Moisture Index (*NDMI*) (B).

Variación por año de los valores promedio de los índices de vegetación por predio. Índice de Vegetación de Diferencia Normalizada (*NDVI*) (A). Índice de Diferencia Normalizada de Humedad (*NDMI*) (B).

lues ranging from -0.118 to -0.057 in the period 1999-2023. From 2011 onward, most properties showed significant increases, which continued until 2023 (Figure 5B).

DISCUSSION

The accuracy of the surface classification results in the Santiago River sub-basin was acceptable, with overall accuracy index values exceeding 0.8. These values are comparable to the 0.83 reported by Sandoval-García et al. (2021) in their multitemporal analysis of Cumbres de Monterrey National Park, Mexico. The Kappa index also indicated an acceptable classification, as moderately high values were obtained (0.61-0.80), indicating a good correlation among the samples. These values are higher than the 0.76 reported by Hernández-Cavazos et al. (2023) in an analysis of land use change in the municipality of Linares, Mexico.

Historically, Durango has been recognized as the largest timber producer in Mexico, contributing about 28.9% to the country's total production. According to the agricultural census results, forest production in 2022 amounted to 4,173,804 m^3 of pine and 796,386 m^3 of oak (INEGI, 2022). This is particularly relevant as forests (comprising oak, oak-pine, pine, and pine-oak) accounted for more than 67% of the land cover in the Santiago River sub-basin throughout the years analyzed. However, changes in land use and vegetation cover from 1999 to 2023 have been constant, altering the landscape of this region.

Using the year 2011 as a reference, when soil conservation and restoration initiatives increased, it was observed that pine forests encompassed an area of 80,901 ha, highlighting the abundance and significance of pine species. In Durango, the main tree species harvested are pine and, to a lesser extent, oak (López-Serrano et al., 2022). Following 2011 (from 2011 to 2023), the area covered by pine forests remained stable and even grew by 1,898 ha, with a rate of change of 0.19% per year. This indicates the regeneration capacity of these forests and the effectiveness of implemented actions, as many efforts included reforestation, particularly of pine species. Some authors suggest that combining soil conservation practices with reforestation has a positive impact on forests, making reforestation a viable option when economic resources for other recovery methods are limited (Ventura-Ríos et al., 2017).

The most significant degradation occurred in pine-oak and oak forests, which experienced a combined loss of 11,690 ha, with annual rates of change of -1.03% and

-0.49%, respectively, from 1999 to 2011. After 2011, the rate of change in pine-oak forests remained negative, albeit a reduced rate (-0.89%), while oak forests showed signs of recovery, indicating that the degradation of these forests had decreased. Notably, oaks hold considerable economic and ecological importance; for instance, their wood is the second most harvested (Cuevas-Reyes et al., 2024) and they provide habitat for various species of fauna (Steele, 2021), although pine species are generally favored in forest management and reforestation campaigns where high-value species are typically used (Moctezuma-López & Flores, 2020).

It is important to consider that reforested areas are subsequently harvested, hindering ecosystem recovery. Similar trends have been observed in other watersheds in northern Mexico. For instance, from 1985 to 2016, the oak and mixed forests of the Conchos River basin showed high rates of degradation and deforestation (-27.7%), along with a 42% increase in agricultural areas (Peña et al., 2022). Regarding the rate of change, it has been reported that prior to 2011 (during the 1992-2002 period), some pine and oak forests in the Upper Nazas River Basin exhibited rates of change of -8.6% and -8.9%, respectively, while shrublands and grasslands saw increases of over 10% (Solís-Moreno et al., 2006). This is relevant because the annual change rates for pine and oak forests reported in this study are higher, suggesting forest recovery, while the rates of shrubland and grassland have decreased.

Although the landscape of the sub-basin changed during the evaluation period, the area of bare soil has decreased. By 2011, it had decreased by 1,106 ha, i.e., a negative rate of change; following that year, it decreased by another 203 ha (2011-2023). This suggests that, although slowly, the vegetation cover in the watershed has been recovering. Some authors have noted that while soil recovery is gradual, the improvement in soil quality is increasing, allowing for the accumulation of organic matter and positively impacting plant regeneration (García-Gallegos et al., 2023).

The proportion of land use and vegetation classes varied across forest properties in the sub-basin and showed surface area changes each year. The variation in surface areas from one property to another was primarily influenced by their location. For instance, properties C, D, E, F, G, and J are mostly situated in forested areas and, therefore, possess a greater area of forest compared to properties with significant amounts of other land uses and vegetation. Additionally, the increase in pine forest areas in some properties during 2023 may be attributed to the reforestation campaigns carried out in the region (Aguirre-Calderón et al., 2015).

In analyses of land use and vegetation changes, which often assess deforestation, both forested and non-forested areas are taken into account. However, it is essential to note that a forest does not always convert directly to bare soil; rather, it can lose or regain coverage of other types of surfaces over time, becoming degraded or recovering (Pimienta-Ramírez et al., 2025). The study area is an example of a dynamic system where land uses and vegetation continuously replace one another, with forested areas gradually transitioning into surfaces covered by mixed forests, scrubland, grasslands, or bare soil.

The greatest stability in land use and vegetation was observed in areas designated for human settlements, grasslands, and pine forests. In contrast, oak and pine-oak forests exhibited the least stability. From 2011 to 2023, the permanence of pine forests was recorded at 66%, while oak forests saw only 38%. This trend may be linked to the reforestation efforts primarily involving pine species. As an example, in 2013, a plantation on property E involved the planting of 437,636 pine trees across an area of 459 ha (CONAFOR, 2018), suggesting that reforestation is a key reason for the increased pine forest cover observed in property E in 2023. Moreover, the Pinaceae family has been recognized as the most representative and widely spread in this region (López-Serrano et al., 2022). On the other hand, agricultural land also exhibited high permanence, especially between 2011 and 2023. According to ECLAC (2021), the transformation of tree vegetation into agricultural land and grasslands is a leading cause of forest loss in Latin America. However, it is noteworthy that agricultural areas are often abandoned, resulting in the increase or recovery of other land uses and vegetation types (forests, scrubland, grasslands, and bare soil). Despite this, agriculture remains one of the principal drivers of land use and vegetation change (Sahagún-Sánchez & Reyes-Hernández, 2018).

Low values of spectral indices can be partially attributed to the dry season, characterized by a scarcity of herbaceous plants and agricultural activity. The average *NDVI* values across the 11 properties showed similar patterns of increase and decrease. In all years, the values remained below 0.2, indicating areas with low vegetation density, which may be disturbed or exhibit low photosynthetic activity (Ruan et al., 2022). Additionally, low *NDVI* values imply reduced vegetation abundance across nearly all cover types, including dense forests, which typically record values above 0.5 (Ceceña-Sánchez et al., 2021). All properties feature areas of agriculture, grassland, and bare soil (Figure 4), directly affecting the average *NDVI* value, especially in regions devoid of vegetation or with dry vegetation. From 1999 to 2023, *NDVI* values showed an upward trend, notably higher from 2011 to 2023, indicating an increase in photosynthetic activity and suggesting a recovery of vegetation. However, it is important to highlight that conservation and restoration efforts have intensified on these properties since 2011, which could have contributed to this increase.

Plant survival in reforestation areas should also be considered. In Mexico, it is estimated that reforested areas achieve a low (36%) or medium (50%) survival rate

(Burney et al., 2015) in the initial years, often due to poor plant quality and drought conditions. In this regard, the region has encountered moderate to severe droughts recently, with an overall decrease in precipitation (CONAGUA, 2024). Zhang et al. (2016) found a positive relationship between *NDVI* and precipitation; under drought conditions, plants experience water stress leading to decreased *NDVI* values. In addition, Durango has faced a rise in forest fires, with over 240 recorded annually until 2011, affecting areas even larger than 100 ha, including the Upper Nazas River basin (SEMARNAT, 2023).

The *NDMI*, which indicates vegetation water stress, recorded negative average values across all properties and in every year, consistently falling below -0.02. This suggests low moisture content in the vegetation. Values ranging from -0.2 to 0 indicate medium-low canopy cover and high-water stress (Jin & Sader, 2005). Over time, the forest properties exhibited a trend of increasing canopy cover. Some researchers suggest that the rise in spectral index values indicates a vegetative recovery (Pesaresi et al., 2020). However, water stress persisted, as no positive *NDMI* values were observed in any property. Zhang et al. (2016) noted that as *NDVI* and *NDMI* increase, the condition of vegetation in an ecosystem improves. This indicates a generally proportional relationship, i.e., a greater presence of vegetation corresponds with a higher moisture content. Thus, it can be confirmed that although some land uses and vegetation types did show an increase in coverage, water stress remained widespread.

CONCLUSIONS

The multitemporal analysis conducted in the Santiago River sub-basin of Durango offers an in-depth examination of land cover and vegetative dynamics from 1999 to 2023. The predominant presence of pine forests indicates a higher level of stability within these ecosystems, likely attributable to effective reforestation efforts. In contrast, oak and pine-oak forests exhibit a significant trend toward degradation, suggesting limited benefits from reforestation activities in the region. Notably, the reduction in bare soil area indicates a recovery in vegetation cover. On the other hand, spectral indices corroborate this recovery; however, persistent evidence of water stress was identified across the 11 properties evaluated.

Despite the observed recovery of vegetation cover, the evidence of water stress represents challenges for the long-term sustainability of the sub-basin's forests. These findings highlight the importance of ongoing monitoring and management strategies to ensure the ecological health and functionality of these ecosystems.

AUTHOR CONTRIBUTIONS

GGÁ: original idea, data analysis and preparation of the manuscript; BVL: data analysis, revision of the manuscript and coordination of revisions; PCC: data analysis and revision of the manuscript; JJGL: revision of the manuscript.

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