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Change of vegetation cover and land use of the Pómac forest historical sanctuary in northern Peru

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Abstract

The dry forests of northern Peru, in the regions of Piura, Tumbes, Lambayeque, and La Libertad, have experienced significant changes as a result of deforestation and changes in land use, leading to the loss of biodiversity and resources. This work analyzed for the first time the changes in vegetation cover and land use of the Pómac Forest Historical Sanctuary (PFHS), located in the department of Lambayeque (northern Peru). The employed approach was the random forest algorithm and visually interpreted Landsat satellite images for the periods 2000–2002, 2002–2004, and 2004–2008. Gain and loss rates were computed for each period, and the recovery process was assessed using the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI). Results indicate an expansion of agricultural land during each period, resulting in the deforestation of 102.6 hectares of dense dry forest and 739.9 hectares of open dry forest between 2000 and 2008. The degree of reforestation in the cleared areas was measured using the NDVI and EVI indices, revealing an improvement from 0.22 in NDVI in 2009 to 0.36 in 2022, and from 0.14 to 0.21 in EVI over the same period. This study is expected to pave the way for executing land management plans, as well as the use and conservation of natural resources in the PFHS in a sustainable manner.

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Introduction

The tropical dry forest covers 50% of the forested areas in Central America and 22% in South America (Quiroga et al. 2019). This ecosystem is characterized by receiving 80% of its precipitation during the stationary period of four months each year (Maass and Burgos 2011; Espinosa et al. 2012). It is limited by the availability of water resources, especially in South America, but it provides a significant number of ecosystem services (Miles et al. 2006), with one of the main ones being the removal of carbon dioxide (CO_2) from the air (Álvarez-Dávila et al. 2017). However, land use change has made it one of the most threatened ecosystems (Renzo 2003), due to fragmentation and transformation, resulting in a 25% reduction of its original extent (Adán et al. 2014; Stan and Sanchez-Azofeifa 2019), making it one of the most endangered biomes on the planet (Maass and Burgos 2011).

In Latin America, dry forest ecosystems face significant challenges due to deforestation and forest degradation (Jiménez et al. 2019). Additionally, they are constantly disturbed by human activities, particularly various agricultural practices (Alejandra and Romero 2016). In Peru, dry forests

cover 3.11% of the national territory (MINAM 2022), but they are facing deterioration primarily due to illegal human settlements and economic activities (SERNAP 2016a). In the northern coastal region of the country, in the department of Lambayeque, the Pómac Forest Historical Sanctuary (PFHS), declared a Protected Natural Area (PNA) under D.S. N° 034-2001-AG, is not exempt from this issue. In 2001, there was an illegal human settlement in the area. The invaders cleared approximately 25% of the sanctuary's area for agricultural activities, as well as for building homes and roads to transport their products for commercialization. It is important to note that the agricultural activities were carried out using groundwater through the construction of tube wells (Ramírez et al. 2020). In response to these events, in 2009, an order was issued to evict around 800 invaders. After this incident, the sanctuary was granted legal security over its territory to ensure its integrity and facilitate physical sanitation and recovery efforts. (Source: https://andina.pe/agencia/noticia-policia-realiza-vuelo-reconocimiento-sobre-santuario-historico-bosque-pomac-214550.aspx).

Remote sensing is defined as a technique through which images are acquired, processed, and visually or digitally interpreted to extract information about the land cover and land use in a specific area (Astudillo-Sánchez et al. 2020). It presents advantages over traditional methods due to its rapid processing of large volumes of data, facilitating decision-making (Cuello et al. 2015). Moreover, it is a cost-effective alternative (Zhu et al. 2019). However, it is limited by factors such as spatial and tem-poral resolution, as well as images

availability (Gevaert et al. 2015). Satellite sensor images were used to map land cover and land use more accurately using the random forest algorithm (Zhao et al. 2019). This enabled the evaluation of forest resources and human settlements, discriminating soil conditions, vegetation types, and their states, thus detecting and interpreting land use changes for biomes conservation (Stan and Sanchez-Azofeifa 2019).

To date, land use changes and vegetation recovery information is extremely limited in Peru. The present study aims to analyze land use changes and vegetation recovery in the Pómac Forest Historical Sanctuary between 2001 and 2022, using Landsat images, the random forest classification algorithm, and multitemporal analysis based on multi-spectral indices. Additionally, it will visualize the process of natural recovery after anthropogenic occupation. This study seeks to be a valuable tool for improving the management of PFHS and may be replicated in other ANPs in tropical dry forest ecosystems or similar environments in Peru.

Materials and methods

Study area

The study encompasses a total area of 5887.4 hectares located in the Pómac Forest Historical Sanctuary (PFHS), in the lower part of the La Leche river, Pitipo district, Ferreñafe province, Lambayeque department, Peru (Fig. 1), with a maximum altitude of 240 m a s l between the geographic

Fig. 1 Location of the study area in the Lambayeque region in northern Peru
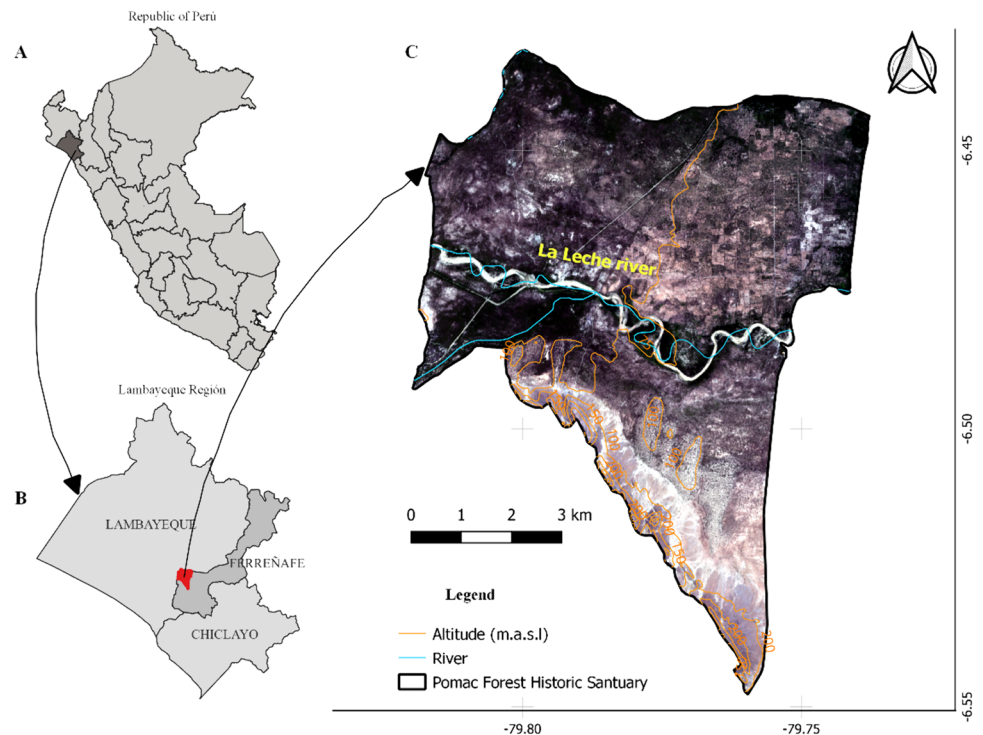
coordinates 6°25′55.49″ and 6°32′51.84″ South Latitude, 79°44′15.75″ and 79°49′10.92″ West Longitude. The multitemporal analysis was carried out considering the years 2000, 2002, 2004, and 2008, presenting minimum temperatures of 11.5 °C (July and August), and maximum of 33.1 °C (December–May); average rainfall of 1078 mm, concentrated in the months of March and April. It should be noted that the maximum values of rainfall are recorded in the years that El Niño-Southern Oscillation (ENSO) occurred (SERNAP 2016a, b).

Spatial Information and workflow flowchart

Spatial information was obtained from remote sensors from the Landsat 5 and Land-at 7 satellites (Table 1) of the United States Geological Survey (USGS), with a spatial resolution of 30×30 m. for the elaboration of land use and vegetation cover maps.

The selection of remote sensing images was made considering the following criteria, as reported by Chuvieco (1996): (i) Maximum 10% cloudiness and shadow, (ii) absence of distortions, and (iii) belong to the same time of the year. In addition, to define the study area, we used: (i) the limits of National System of Natural Areas Protected by the State (SERNANP for its acronym in Spanish), and (ii) the Digital Elevation Model (DEM) with a resolution of 12.5×12.5 m of the ALOS PALSAR (Phased Array Type L-band Synthetic Aperture Radar) platform. The processing of Landsat images was conducted using the open-source software QGIS, and the vegetation cover and human settlements were calculated using the random forest plugin (Hantson et al. 2011). The sequential procedure followed in the study is shown in Fig. 2.

Land use change

For land use change, the random forest (RF) algorithm was employed, as it is widely used and has demonstrated good thematic accuracy (Zhao et al. 2019; Ramírez et al. 2020). Together with the PFHS map (SERNAP 2016a), five classes of land use coverage (LUC) were identified: dense dry forest (DDF), sparse dry forest (SDF), agricultural land (AL) and bodies of water (BW) (Table 2). The calibration of the
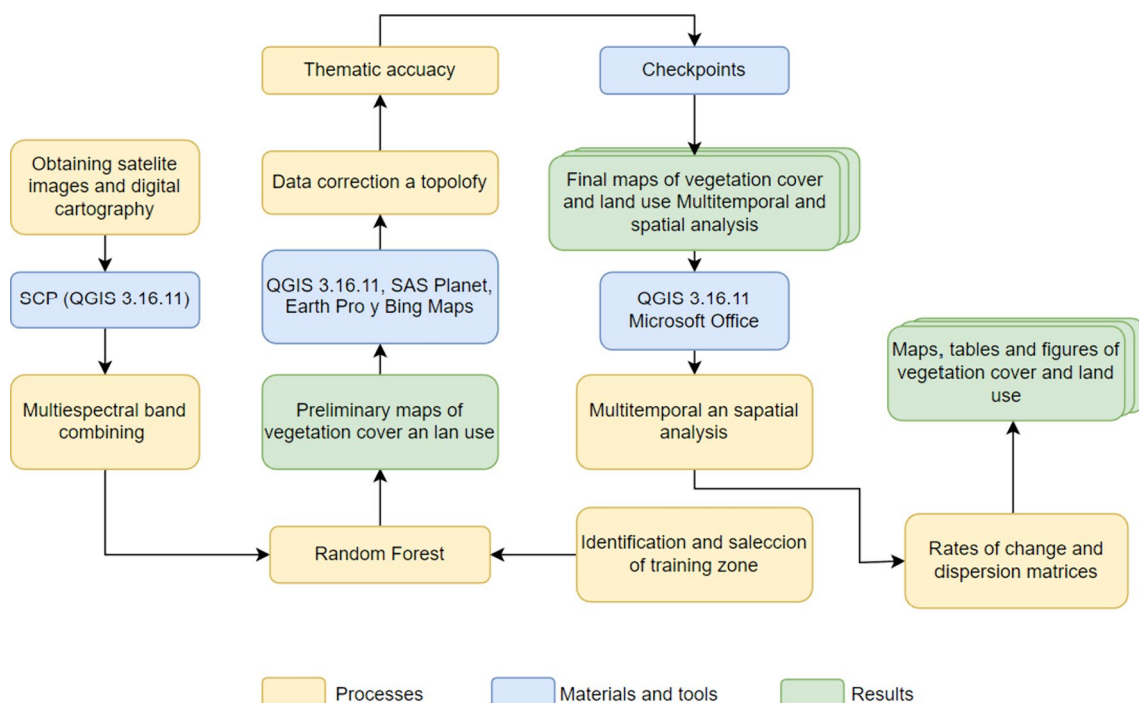
Table 1 Images from satellite sensors for the period 2000–2008 in the study area

Acquisition date	Satellite/sensor	Path/row	Spectral band
October 07, 2000	Landsat 5 TM	10/65	1,2,3,4,5 y 7
September 03, 2002	Landsat 7 TM	10/65	1,2,3,4,5 y 7
August 15, 2004	Landsat 5 TM	10/65	1,2,3,4,5 y 7
May 06, 2008	Landsat 5 TM	10/64	1,2,3,4,5 y 7

Fig. 2 Methodological workflow to analyze changes in vegetation cover and land use in the dry forest of the Pómac Forest Historical Sanctuary (PFHS) in northern Peru

Table 2 LUC classes identified in the PFHS using the CORINE Land Cover methodology adapted for Peru. Source: own elaboration based on MINAM (2015)

Level I	Level II	Level III	LUC
2. Agricultural areas	2.1.1 Farmland	2.1.1. Permanently irrigated land	AL
3. Forests and mostly natural areas	3.1 Forests	3.1.1. Low dense forest	DDF
		3.1.2. Low sparse forest	SDF
		3.1.5. Fragmented forest	
	3.3 Open spaces with little or no vegetation	3.3.4 Bare land	BL
5. Water surfaces	5.1 Inland water	5.1.2. Lagoons, lakes and permanent natural swamps	BW

AL agricultural land, *DDF* dense dry forest, *SDF* sparse dry forest, *BL* bare land, *BW* bodies of water

classification was carried out based on spectral signatures of 157 regions of interest within the PFHS. Among these regions, 28 points correspond to areas of dense dry forest (DDF), 80 to sparse dry forest (SDF), 24 to agricultural land (AL), 2 to bodies of water (BW), and 23 to bare soil using six bands of the visible and infrared spectrum of the remote sensors of the Landsat satellites. The spectral distances of the regions of interest were assessed using the Jeffries–Matusita (JM) distance in a range from 0 to 2, where the values that tend to 2 present different spectral signatures (Santana et al. 2014).

Thematic accuracy

The validation of the thematic classification aims to obtain the quantitative description of the accuracy achieved during the process (Moreno and Chuvieco 2009). The selection of samples and determination of relationships between the assigned cover and the reference cover is obtained through the construction of the confusion matrix, which indicates the level of correspondence between the relationships (Strahler et al. 2006). The importance of it is that it allows us to capture the main conflicts between categories (Congalton and Mead 1983).

The analysis of multiple relationships between classes was carried out using the Kappa statistic, which measures the difference between the map and the observed reality, through the following equation (Pontius et al. 2004):

$$k = \frac{m \sum_{i=1,n} X_{ii} - \sum_{i=1,n} X_{i+} X_{+i}}{m^2 - \sum_{i=1,n} X_{i+} X_{+i}} \tag{1}$$

where, n is the number of rows in the matrix; X_{ii} the number of observations in row i and column i; $X_i + X + i$ are the marginal total of row i and column i, respectively, and m is the total number of observations.

Spatiotemporal intensity of the rate of change and transition matrices

The transition matrix allows the analysis of the annual rate of land use change between two different periods, through the equation proposed by Anand et al. (2020), for the identification of the main transitions and detection of changes in the evaluated classes (Pontius and McEachern 2004). The negative values of the equation indicate a decrease in LUC, on the contrary, a positive value indicates an increase in it, and it is calculated as follows:

$$S = \left(\frac{S2}{S1}\right)^{\frac{1}{t2-t1}} - 1 \tag{2}$$

where, $S1$ and $S2$ are the LUC surfaces at date $t1$ and $t2$.

The obtained results were as follows: (i) exchange (Int) between classes, in which the gain of one type of coverage implies the loss of another; (ii) gain (Gj) is estimated, based on the differences in the total area of each class j on date 2 ($P+j$), and (iii) the persistence that is expressed in the diagonal of the matrix (Pjj). The loss (Li), is the difference between the total area of a class i at date 1 ($Pi+$) and the persistence. To estimate the total change at the class level (Ct), the gains (Gj) and the losses (Li) are added, while, for the net change, which indicates a definitive change, it is represented as the difference between the total change (Ct) and the exchange (Int) (Table 3, 4, and 5).

Multitemporal monitoring

For the assessment of the recovery process of the PFHS, following the population occupation it underwent between the years 2001 and 2009, a multitemporal analysis of vegetation indices from Landsat images was conducted. These images were obtained through the geospatial analysis

Table 3 Cross tabulation matrix for LUC in the period 2000–2002

2000	2002					Total 2000 (ha)	Exchange rate	Loss (Li)	Total, change (T_c)	Net change (N_c)	Interchange (Int)
	DDF	SDF	BW	AL	BL		%				
DDF	1,010.49	69.31	1.50	9.77	2.39	1,093.46	23.66	7.59	68.08	52.91	15.18
SDF	638.37	2,679.35	6.04	72.04	29.16	3,424.96	−5.34	21.77	33.15	10.39	22.76
BW	4.37	10.92	9.77	0.75	3.99	29.80	−9.00	67.21	117.25	17.18	100.07
BL	18.77	309.47	7.37	21.65	981.65	1,338.91	−12.84	26.68	29.34	24.03	5.31
Total 2002 (ha)	1,672.00	3,069.05	24.68	104.21	1,017.19	5,887.13					
Gains (Gj)	60.50	11.38	50.03	104.21	2.65						

DDF dense dry forest, *SDF* sparse dry forest, *AL* agricultural land, *BL* bare land, and *BW* bodies of water

Table 4 Cross tabulation matrix for LUC in the period 2002–2004

2002	2004					Total 2004 (ha)	Exchange rate	Loss (Li)	Total, change (T_c)	Net change (N_c)	Interchange (Int)
	DDF	SDF	BW	AL	BL		%				
DDF	1,295.75	342.68	0.76	32.65	0.14	1,671.98	−4.07	22.50	37.02	7.98	29.04
SDF	236.62	2,536.01	5.28	270.73	20.40	3,069.04	1.36	17.37	37.48	2.75	34.74
BW	2.19	13.07	8.90	0.00	0.51	24.67	4.39	63.91	136.81	8.98	127.83
AL	0.00	0.00	0.19	104.01	0.00	104.21	67.75	0.19	293.41	293.04	0.37
BL	3.99	261.55	11.76	2.18	737.71	1,017.18	−13.63	27.47	29.54	25.41	4.14
Total 2004 (ha)	1,538.55	3,153.31	26.89	409.58	758.76	5,887.08					
Gain (Gj)	14.52	20.11	72.89	293.23	2.07						

DDF dense dry forest, *SDF* sparse dry forest, *AL* agricultural land, *BL* bare land, and *BW* bodies of water

Table 5 Cross tabulation matrix for LUC in the period 2004–2008

2004	2008					Total 2004 (ha)	Exchange rate	Loss (Li)	Total, change (T_c)	Net change (N_c)	Interchange (Int)
	DDF	SDF	BW	AL	BL		%				
DDF	905.02	558.17	11.90	60.27	3.46	1,538.81	− 16.88	41.19	51.46	30.91	20.55
SDF	155.35	2,383.81	30.47	397.08	186.60	3,153.32	− 2.55	24.40	43.77	5.03	38.74
BW	1.37	7.46	16.04	0.38	1.63	26.89	49.46	40.34	204.08	123.40	80.69
AL	0.00	0.00	0.62	408.79	0.00	409.40	45.94	0.15	113.29	112.99	0.30
BL	1.36	45.12	1.04	5.48	705.75	758.76	8.76	6.99	32.25	18.28	13.97
Total 2008(ha)	1,063.11	2,994.57	60.07	872.00	897.45	5,887.18					
Gain (Gj)	10.27	19.37	163.74	113.14	25.26						

DDF dense dry forest, *SDF* sparse dry forest, *AL* agricultural land, *BL* bare land, and *BW* bodies of water
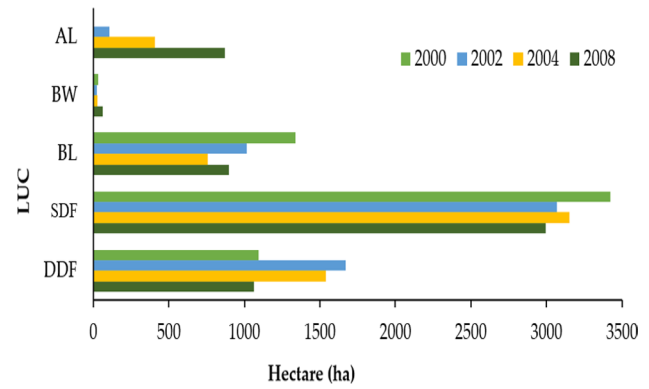
Fig. 3 Space–time dynamics of coverage and land use for the years 2000, 2002, 2004 and 2008 of the PFHS. Where AL (agricultural land), DDF (dense dry forest), SDF (sparse dry forest), BL (bare land) and BW (bodies of water)

platform, Google Earth Engine (GEE). The obtained indices represent annual average values for the years 2009–2022.

Through this evaluation, the aim was to demonstrate the recovery process of tropical dry forests that have experienced deforestation. The following indices were used:

(a) Normalized Difference Vegetation Index (NDVI).

Anand et al. (2020) stated that NDVI is one of the most widely used indices and exhibits good efficiency for analyzing vegetation of both high and low density.

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \tag{3}$$

(b) Enhanced Vegetation Index (EVI).

EVI is an optimized vegetation index, originally developed as an improvement over NDVI. It is used to achieve greater sensitivity in the high biomass region by de-coupling background variables and atmospheric influences (Anand et al. 2020).

$$\text{EVI} = 2.5 * \frac{\text{NIR} - \text{RED}}{\text{NIR} + 2.4 * \text{RED} + 1} \tag{4}$$

Results and discussion

Evaluation of land use change in the PFHS

Land use change (LUC) studies allow us to know the different processes that the territories are going through, being the

economic activities practiced by different societies the main causes of environmental deterioration (Squeo et al. 2007). The Pómac Forest Historical Sanctuary suffered a population invasion for almost 10 years, which destroyed 29% of the original vegetation cover. Since year 2009, the SERNANP has implemented actions for the protection and regeneration of plant cover.

Figure 3 shows the spatiotemporal dynamics of land use and cover Changes (LUCs) in the Pómac Forest Historical Sanctuary using 2000 as the base year. The following patterns are evident: (i) Dense Dry Forest (DDF) exhibits an increase of 52% by the year 2002, followed by a decrease of 8% in 2004, and a further reduction of 44.7% in 2008 compared to the year 2004, (ii) Sparse Dry Forest (SDF) shows a decrease of 10.4%, 7.9%, and 12.6% for the years 2002, 2004, and 2008, respectively, relative to the base year, (iii) (iv) Bare Land (BL) exhibits a similar behavior to SDF, and

(v) Agricultural Land (AL) is evident from the year 2002 with 104.2 hectares, increasing to 409.6 hectares by 2004, and further expanding to 872.1 hectares by 2008.

The graphic representation of the different land uses in the PFHS during 2000, 2002, 2004 and 2008 is shown in Fig. 4. The coverage of DDF presents a decreasing variation for the years evaluated, being its occupied areas mainly for the AL and SDF cover. The changes occurred in the different vegetation covers that comprise the PFHS are significantly related to the process of population invasion and natural phenomena (Holmgren and Scheffer 2001). The dense dry forest (DDF) for the year 2002 shows a significant increase due to the rise in precipitation in the northern coast of Peru (Squeo et al. 2007). From the period 2000 to 2008, a reduction in vegetation cover of the SDF and DDF is evident, with fluctuations of increases and decreases during each analysis period. Additionally, in the

Fig. 4 Pómac forest historical sanctuary land use change maps, **a** 2000, **b** 2002, **c** 2004 and **d** 2008
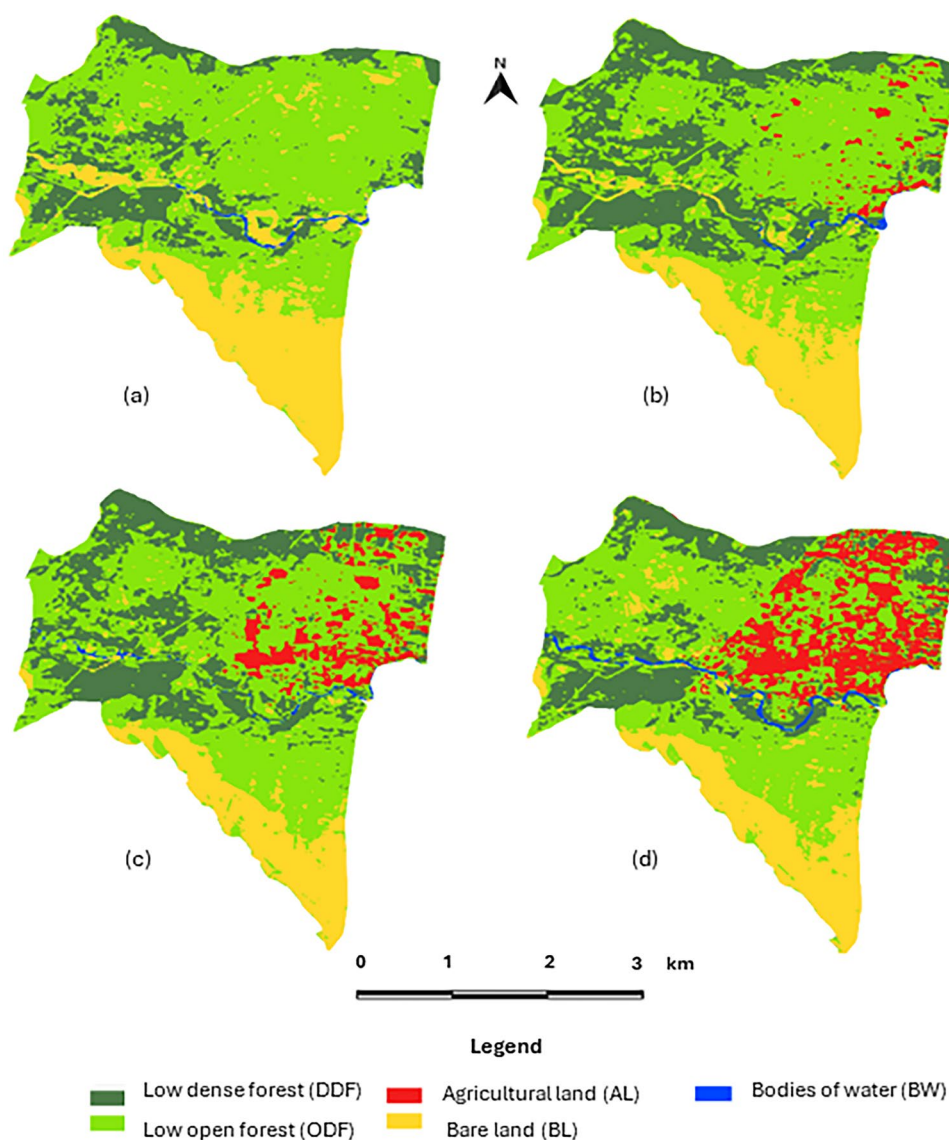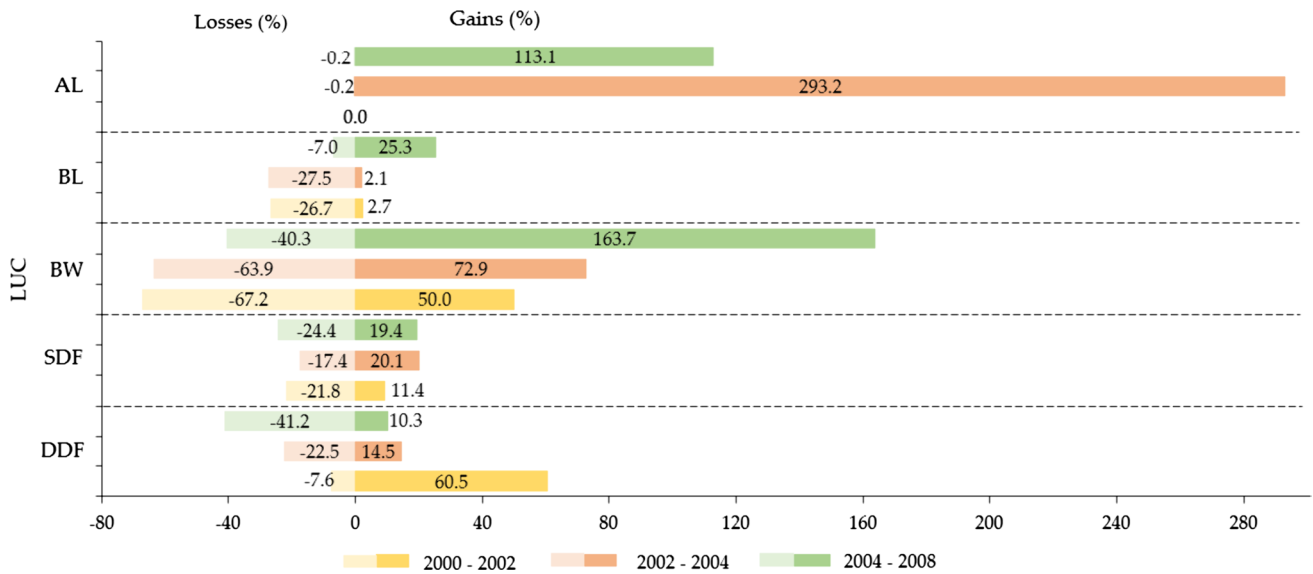
Fig. 5 Gains and losses for period: 2000–2002, 2002–2004 and 2004–2008. LUC (land use change); AL (agricultural land), DDF (dense dry forest), SDF (sparse dry forest), BL (bare land) and BW (bodies of water)

year 2008, the SDF decreased by 430.3 ha because of population invasion, leading to logging activities for charcoal production and other logging practices (SERNAP 2016a, b). The tabulation matrix for the first period (2000–2002) shows a positive rate of change for the dense dry forest (DDF) coverage (23.66%) and negative rates for sparse dry forest (SDF) (− 5.34%) and bare land (BL) (− 12.84%) coverages. By the year 2002, the impacts generated by agricultural activity within the Pómac Forest Historical Sanctuary can already be observed, with an approximate area of 104.21 hectares of agricultural land (SA) (Table 3).

The dense dry forest (DDF) is the vegetation cover that shows the highest surface change at 68.08%, with a gain of 60.5% and a loss of 7.59% (Fig. 5). The second cover that underwent changes is the Sparse Dry Forest (SDF) with 33.15%, experiencing a loss of 21.77% and a gain of 11.38% relative to the base year.

In the second period (2002–2004), a positive rate of change is observed in agricultural land (AL) with a net change of 293.41%, indicating a gain of 409.58 hectares of agricultural coverage. During this period, there was deforestation of 270.73 hectares of sparse dry forest (SDF) and 32.65 hectares of dense dry forest (DDF) (Table 4). Dense dry forest (DDF) experienced a loss of 22.5%, followed by sparse dry forest (SDF) with 17.37% (Fig. 5). These losses

were mainly attributed to anthropogenic activity within the Pómac Forest Historical Sanctuary.

In the third period (2004–2008), a negative rate of change is observed for dense dry forest (DDF) (− 16.88%) and sparse dry forest (SDF) (− 2.55%) coverages. On the other hand, there is a positive rate of change for (AL) (45.94%), (BW) (49.46%) and (BL) (8.76%) (Table 5). The AL presented a gain of 113.14%, which is attributed to a deforestation of the DDF and SDF vegetation covers with losses of − 41.19% and − 24.40%, respectively. Additionally, during this period, the SD evidenced a gain of 25.26% (Fig. 5). Throughout the analysis period, the deforestation of 102.6 hectares was identified for DDF coverage, while for ODF a reduction of 739.9 hectares was observed, as a result of agricultural expansion in the PFHS.

Calibration and validation of land use coverage (LUC)

The degree of differentiation or similarity of the LUC classes present a range of 0.98–2.0. The covers of DDF and SDF present a similarity due to the scarce presence of leaves. After that, a visual correction was performed. The global accuracy for the classification of multispectral images (Landsat 5 and Landsat 8) in the years 2000, 2002, 2004 and

2008 was 95.39, 95.61, 96.71 and 94.08%, respectively. The Kappa index (*k*) was 92.03, 92.87, 94.73 and 91.03 which indicate a high classification agreement (Holmgren and Scheffer 2001). In the confusion matrix for the year 2000, the BW class shows an optimum level of accuracy of 100%. The producer affirms that 96.6, 94.2 and 93.2% of the SDF, BL, and DDF classes were correctly identified. That is, the same user will find that the DDF, SDF and BL classes correspond to field 96.5, 95.5 and 94.2%, respectively.

The confusion matrix for the year 2004 indicates that the BW and AL classes are not discussed as they exhibit an optimal accuracy level of 100%. The producer asserts that 98.3%, 97.1%, and 90.5% of the DDF, SDF, and BL and AL classes were correctly identified, respectively. On the other hand, a different user found that the field observations matched the DDF, SDF, AL, and BL classes at rates of 95.8%, 97.1%, 96.9%, and 96.6%, respectively.

The confusion matrix for the year 2008 shows that the BW class is not discussed since it exhibits an optimal accuracy level of 100%. The producer affirms that 93.9%, 93.6%, 98.5%, and 89.6% of the DDF, SDF, AL, and BL classes were correctly identified, respectively. On the other hand, a different user found that the field observations matched the DDF, SDF, AL, and BL classes at rates of 93.9%, 95.3%, 97.1%, and 85.7%, respectively.

Multitemporal analysis of vegetation indices

The indices that have been used for the temporal evaluation of vegetation over long periods, with good results, are the NDVI and EVI (Ba et al. 2022; Roy 2021; Peng et al. 2017; Li et al. 2010).The multitemporal analysis of NDVI and EVI indices reveals a positive increasing trend, attributed to the biomass growth resulting from the recovery process (Kubota et al. 2021). Figure 6 spatially displays the area that was occupied by human population, located in the Northeast of the PFHS. Through the NDVI analysis, slight recovery trend during the period from 2009 to 2016 is shown, where NDVI values range from 0.2 to 0.3, and EVI values range from 0.14 to 0.20. In the year 2017, there is an increase in both NDVI and EVI values, reaching 0.5 and 0.4, respectively. This increase is associated with higher precipitation due to the ENSO. In the period 2018–2022, the values remain within the range of 3.5–4 for the NDVI and 2.1–2.4 for the EVI. In general, both indices show a recovery trend in deforested areas, revealing an improvement from 0.22 to 0.36 in NDVI, while for EVI 0.14–0.21 in the period 2009–2022. On the other hand, the EVI highlights areas with sparse vegetation and bare soil more distinctly. Both vegetation indices distinguish the year 2017 as an atypical year that significantly contributed to the recovery of the tropical dry forest in the PFHS. The process of human occupation has altered the structure of tropical dry forests, leading to a loss in the diversity of forest species. Notably, NDVI shows higher values than EVI, which, according to Anand et al. (2020), is influenced by soil and leads to an increase in the irradiation of the near-infrared (NIR) band. Consequently, several authors agree that the EVI index provides greater accuracy in forest monitoring (Adán et al. 2014; Anand et al. 2020).

According to the last population census carried out by the National Institute of Statistics and Informatics (INEI for its acronym in Spanish), in 1993 the total population in the district of Pitipo was 14,221 inhabitants. In 2007, the population increased in 20,080 inhabitants; finally, in 2017, the population decreased to 19,651. This factor contributes to increased pressure on forest resources provided by the Pómac Forest Historical Sanctuary. On the other hand, during the period 2002–2007, the Lambayeque region registered 217,139 immigrants, coming from other parts of the country and abroad.

This study contributes to the monitoring of forest resources in Peru, allowing to obtain thematic information which serves as a basis for formulating projects for the management and conservation of forest resources in the Pómac Forest Historical Sanctuary. In addition, this work allows to know the levels of deforestation and degree of conservation in an efficient and precise way. Similar studies can be conducted in other Peruvian ecosystems (Vargas-Sanabria and Campos-Vargas 2018). Complementary studies are needed to monitor tropical dry forests in Peru based on UAVs and multispectral cameras that allow to collect information quickly and accurately with high spatial resolution.
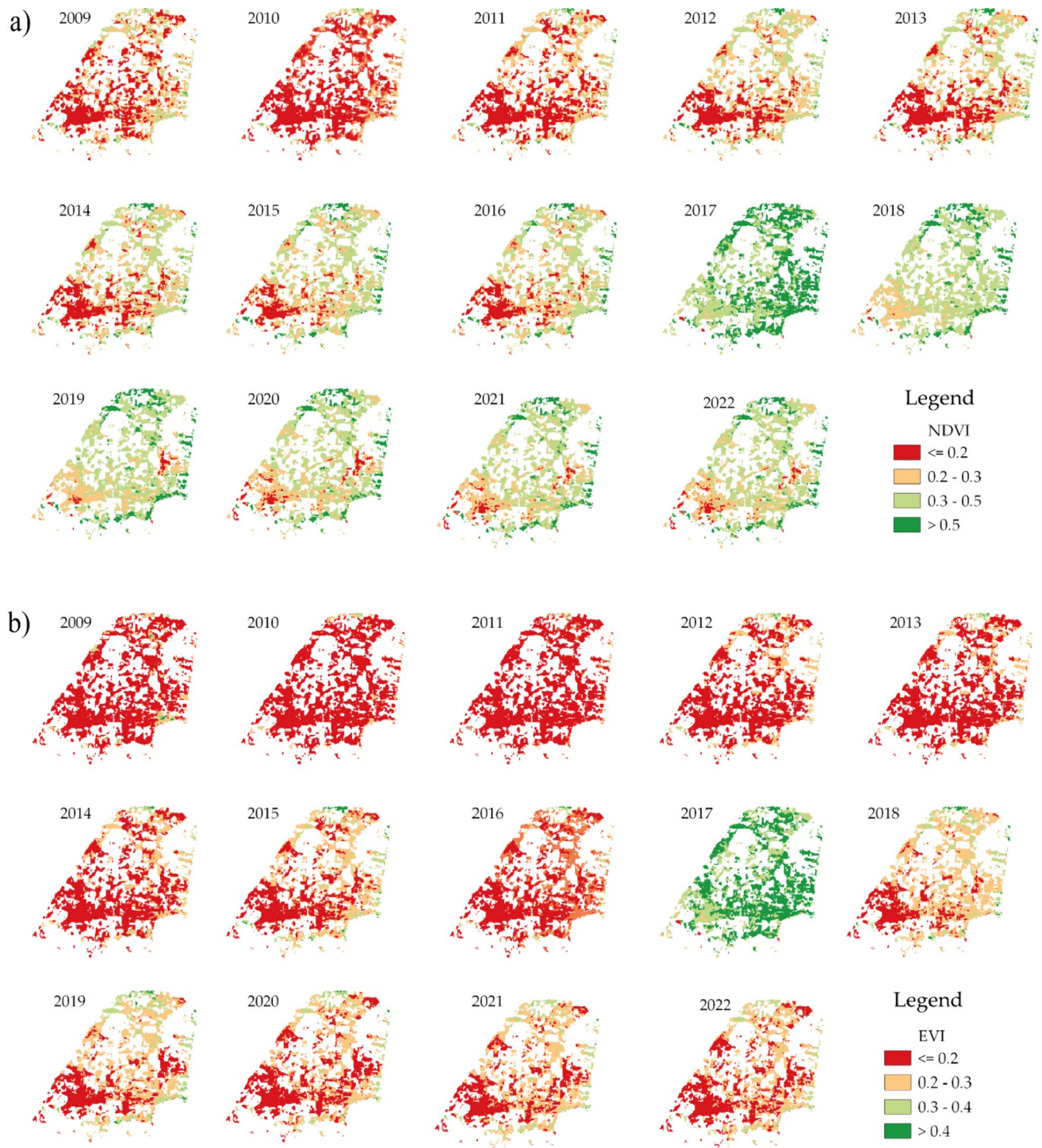
Fig. 6 Annual values of: **a** Normalized difference vegetation index (NDVI) and **b** enhanced vegetation index (EVI)

Conclusion

The classification supervised by random forest showed that there was a change in land use in the period from 2000 to 2008 due to anthropogenic activities, for example, a total of 842.4 hectares of coverage of dense dry forests (DDF) and

sparse dry forests (SDF) were lost, which represents 14% of the total area of the sanctuary. These coverages gave up their areas to intensive agricultural activities carried out by the illegal occupation of the Pómac Forest Historical Sanctuary. After 2008, the NDV and EVI values were used on the Google Earth Engine platform to monitor the recovery of

deforested areas, observing the growth of vegetation in the rainy years caused by ENSO. The recovery of the primary forest is slow, which is why the immediate action of the authorities is necessary for the implementation of forestation programs in the affected areas determined in this study.

Data availability All data generated during this study are included in this published article.

Declarations

Conflict of interest The authors declare no conflict of interest.

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