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Cover and Land Use Changes in the Dry Forest of Tumbes (Peru) Using Sentinel-2 and Google Earth Engine data †

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Abstract: Dry forests are home to large amounts of biodiversity, are providers of ecosystem services and control the advance of deserts. However, globally these ecosystems are being threatened by various factors such as climate change, deforestation and land use and land cover (LULC). The objective of this study was to identify the dynamics of LULC changes, and the factors associated with the transformations of the dry forest in the Tumbes region (Peru) using Google Earth Engine (GEE). For this, the annual collection of Sentinel 2 (S2) satellite images from 2017 and 2021 was analyzed. Six types of LULC were identified, namely urban area (AU), agricultural land (AL), land without or with little vegetation (LW), water body (WB), dense dry forest (DDF) and open dry forest (ODF). Subsequently, we applied the Random Forest (RF) method for the classification. LULC maps reported accuracies greater than 89%. In turn, the rates of DDF and ODF between 2017 and 2021 remained unchanged around 82%. Likewise, the largest net change occurred in the areas of WB, AL and UA of 51, 22 and 21%, respectively. Meanwhile, forest cover reported a loss of 4% (165.09 km2) of the total area in the analyzed period (2017 - 2021). The application of GEE allowed to evaluate the changes in forest cover and land use in the dry forest and from this, it provides important information for the sustainable management of this ecosystem.

Keywords: Forest remote sensing; Random Forest (RF); Temporal series; Biodiversity

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1. Introduction

The dry forest plays an important role in the provision of ecosystem services such as the conservation of endemic flora and fauna species, medicinal plants, wood, firewood and plant foods [1,2]. It is made up of deciduous vegetation, where most of the dominant tree species eliminate approximately 75% of their foliage during the long dry period of the year [3,4]. These forests are also recognized as one of the most threatened ecosystems worldwide [4], as they are exposed to many threats such as deforestation, fragmentation, overgrazing, forest fires, droughts and LULC changes [5,6]. LULC changes exert negative impacts on ecosystems affecting climate, soil, water and air, which are generally induced by the interaction of demographic, socioeconomic, political and biophysical factors [7,8]. The LULC changes affect the loss of ecosystems that are transformed into pastures, crops or new areas of urban expansion. Also, they impact protected areas, reporting high rates of forest loss [9].

Currently, the application of remote sensing (RS) tools plays an important role in analyzing the dynamics of LULC changes through the analysis of medium resolution satellite images such as Landsat and S2 [10]. In recent years, many studies have evaluated the impact of LULC changes in different areas of the world [11,12]. Multi-temporal S2 image processing has been fully exploited on platforms such as GEE [13] through the application of supervised classification using the RF method, with reliable results [14]. In Peru, we find the department of Tumbes that is home to diverse ecosystems such as the dry forest and a diversity of endemic species [15]. However, the forest is exposed to many threats and impacts that are related to human activities [16]. For this reason, the objective of this study was to evaluate the changes in LULC in the dry forest of Tumbes (Peru) using S2 data and the GEE platform in the period from 2017 to 2021.

2. Materials and Methods

2.1. Study Area

The department of Tumbes has an area of 4,646.67 km2 and is located in the north of Peru, between the extreme coordinates of latitude 3°23.045' and 4°13.841' S and longitude of 80° 25.625' and 80° 6.609' W (Figure 1). The study area is part of the dry forest ecosystem and forms the Tumbes region distributed between Peru and Ecuador [16]. It is found in an altitude range that goes from 0 to 1,600 meters above sea level, with a mean annual temperature that oscillates between 20 and 26 °C and annual rainfall between 300 mm in the lowlands and 700 mm in the highlands, respectively [17].

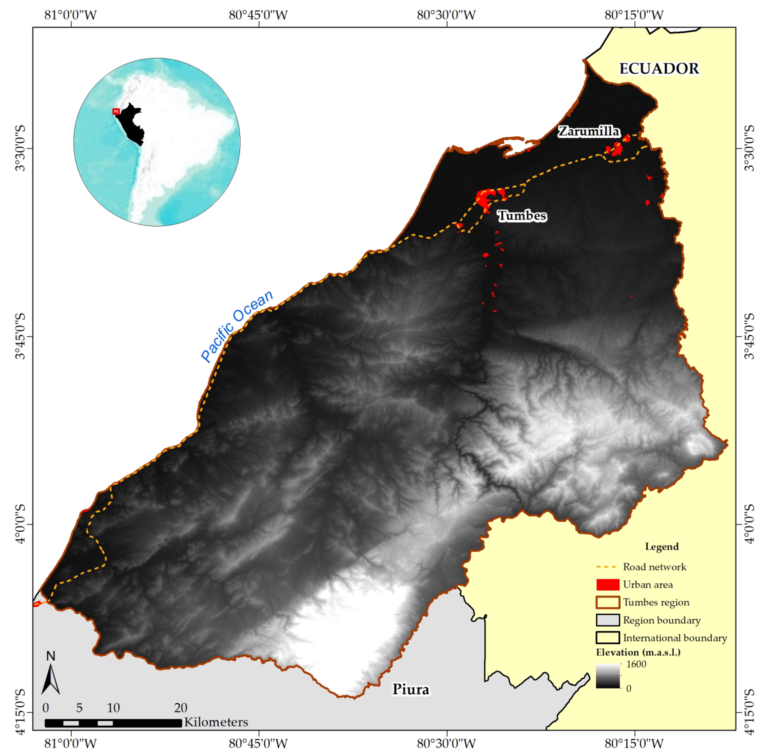

Figure 1. Location of the department of Tumbes in Peru.

2.2. Image acquisition and processing

The data was represented by S2 images from 2017 and 2021 (Figure 2), with a spatial resolution of 10 meters. Image processing was performed in GEE [13]. In order to have a better quality of the S2 images, a filter was applied by metadata considering cloud cover less than 30% [18,19]. Cloud and cloud shadow masking was then performed through the CloudScore and Temporal Dark Outlier Mask (TDOM) algorithms using the Quality Assessment (QA60) band [20]. Subsequently, the vegetation indices were calculated, namely the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Enhanced Vegetation Index (EVI) and Soil Adjusted Vegetation Index (SAVI) with objective to have more variables for the supervised classification process. Finally, the minimum, maximum and median value for each band and vegetation indices were calculated to build a multi-band mosaic for each year.

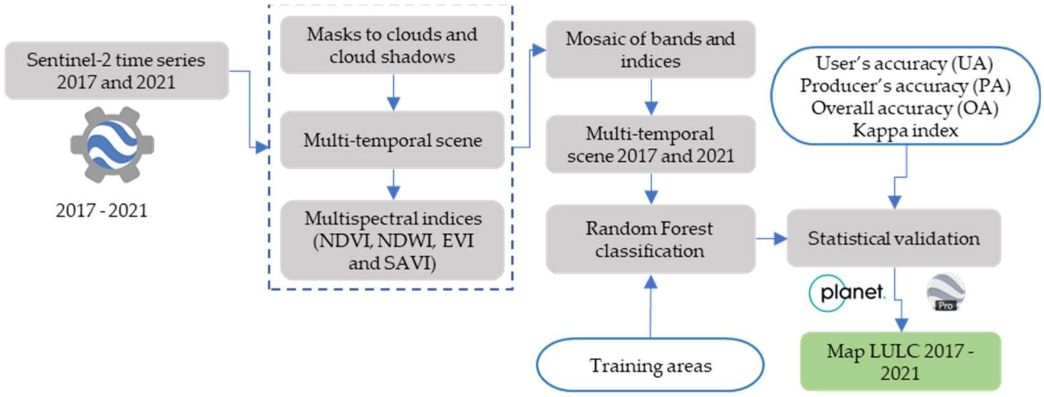

Figure 2. Methodological flow applied to analyze the LULC changes in the dry forest of Tumbes (Peru).

2.3. Classification of images and map of land use and cover change

The training areas were represented by six types of LULC, namely i) urban area (UA), agricultural land (AL), land without or with little vegetation (LW), water body (WB), dense dry forest (DDF) and open dry forest (ODF) that were identified in the field and satellite images. Supervised classification was performed through the RF model. Prior to classification, 20,000 training points were randomly generated, divided proportionally by each type [21] and by year of evaluation. It was necessary to perform a visual analysis of the cartography using high-resolution images in ArcGIS v. 10.5. Subsequently, the intensity, loss, gain and annual rate of change in the analyzed period (2017-2021) [12,22] were determined.

2.4. Validation of the results

The final classified maps were compared with reference data such as Google Earth satellite imagery and PlanetScope using a confusion matrix. For this, 203 randomly distributed validation points were used for each type, assuming a precision error of 3% within a confidence interval of 96%, which allowed calculating the general precision (OA), user precision (UA), precision of the producer (PA) and Kappa index [22].

3. Results

3.1. LULC distribution and accuracy assessment

The 2017 and 2021 LULC maps for the Tumbes region are shown in Figure 3, it is observed that the DDF and ODF types had a larger surface and were distributed throughout the study area with increases from 1,725.02 to 1,822.99 km2 and 1,844.99 to 1,892.01 km2, respectively. The type of AU also reports an increase in its surface from 36.71 to 48.07 km2 for the evaluation years, respectively. However, other classes such as AL located to the northwest and close to water bodies decreased by 92.25 km2 by 2021; In the same way, the LW and WB types showed similar spatial patterns, reporting a reduction in their surfaces of 1.24 and 0.11% according to the years of evaluation. On the other hand, the accuracy of the LULC maps for 2017 and 2021 reported OA values greater than 92%, just as UA and PA were greater than 70 and 71%, respectively. The Kappa index also showed values above 89%.

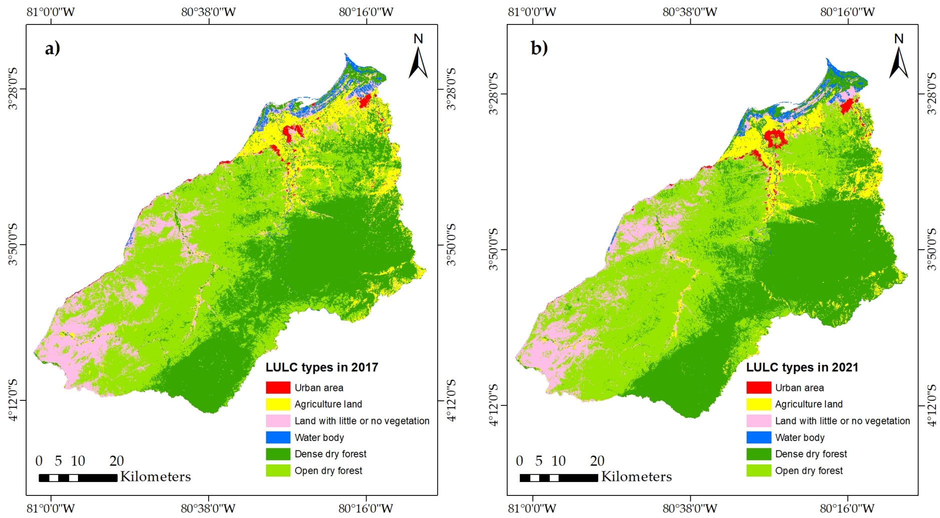

Figure 3. LULC spatial distribution maps for the Tumbes region; a) 2017 and b) 2021.

3.2. Analysis of LULC changes

The analysis of estimated rates for the 2017-2021 period reports a marked dynamic of LULC. The changes mainly occurred in the increase of UA (4.81%), DDF (1.39%) and ODF (0.63). This as a result of the reduction in AL (-5.92%), WB (-1.92%) and BS (-2.67%) rates. Likewise, the greatest changes occurred in UA (55.36%), WB (48.17) and AL (47.03%). In turn, the largest net change was represented by WB, AL and UA of 51.27, 21.67 and 20.66%, respectively. For its part, Figure 4 shows the changes produced by LULC in the analysis period. Consequently, 73% of the forest surface remained unchanged, as did anthropogenic use (agricultural land and urban area) (15%). However, 4% (165.09 km2) of the total area lost its forest cover.

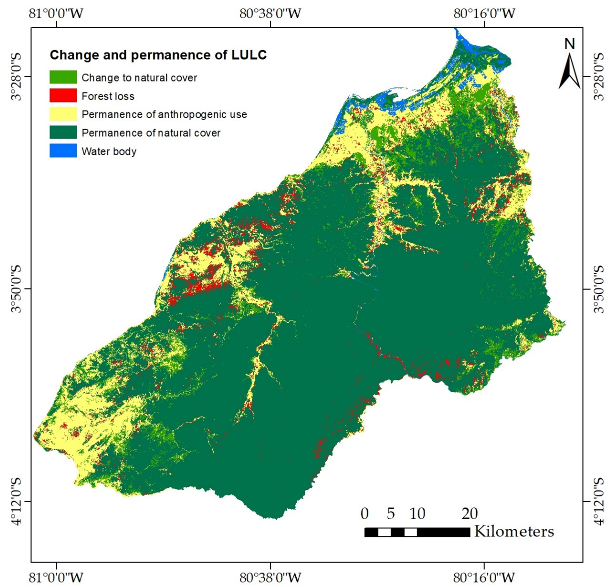

Figure 4. Maps of change and permanence of LULC that occurred between 2017-2021 in the Tumbes region.

4. Discussion

The dry forest of the north coast of Peru is considered the most sensitive region to the El Niño phenomenon (ENP)[23], which mainly affects the populations settled in this ecosystem. Likewise, the vegetation is conditioned by climatic factors, such as precipitation and temperature, since it has a marked effect on the regeneration and physiognomy of the vegetation cover [24]. However, ENP can also bring some positive impacts, especially in rural communities, where they favor some crops such as rice, the appearance of temporary grasslands for cattle, and the regeneration of dry forests [25]. The results of the main types of LULC in the Tumbes region reported an increase in forest cover of approximately 2% by 2021. However, in areas near UA and LW, foci of forest loss were shown. These changes could be related to the expansion of the agricultural frontier, firewood extraction or deforestation [5,24]. Another important aspect is the decrease in the AL surface from 425.65 to 333.40 ha from 2017 to 2021. This reduction could be related to water availability, since the ENP occurred in 2017, which increased the crop plots in the study area.

5. Conclusions

In this study we use 10 m multi-temporal S2 images to analyze LULC changes in the Tumbes region from 2017 to 2021, which were implemented on the GEE platform. The generated maps reported accuracies greater than 89%, which were evaluated with other available high-resolution images. Through the comparison of the LULC maps, it was reported that forest cover in recent years has lost 4% of the total area. In addition, the application of GEE made it possible to evaluate the LULC changes in the dry forest and from this, provide important information for the sustainable management of this important ecosystem.

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Conflicts of Interest: The authors declare no conflict of interest.

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