Original Paper

Projections towards 2050: severe impact of conversion to dragon fruit crops (*Hylocereus spp*. and *Selenicereus spp*.) in the xeric forest

Lizardo Reyna-Bowen, Walther Antonio Cevallos Meza

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Abstract. *Global shifts in land usage have many impacts on ecosystem services and biodiversity. This investigation assessed the transition from 2016* *to 2021 from xeric forest to Dragon fruit (*Hylocereus spp. *and* Selenicereus spp.*) agriculture. To determine the rates of land use change and deforestation, an approach comprising multitemporal analysis, supervised classification of Landsat and Sentinel satellite images, and a transition matrix was used. Furthermore, land use changes up to 2050 were modelled and predicted using Dinamica EGO software. The study noted detrimental effects of dragon fruit cultivation and suggested quick recovery and preservation actions to lessen the startling reduction in forest cover.*

1. Introduction

A wide range of causes, including social, economic, demographic, and environmental ones, are responsible for the global shift of land usage. According to Sahagún & Reyes (2018), this shift has detrimental effects on ecosystem services and biodiversity, including soil degradation, erosion, infertility, and deforestation.

One of the primary effects of changing land use is deforestation, which is bad for the quality of the soil, water, and air (Food and Agriculture Organization [FAO], 2018). Worldwide, 420 million ha of native forests were lost between 1990 and 2020, resulting in a decrease in the percentage of forest cover from 30.8% to 32.5% (FAO, 2020). With an annual deforestation rate of over 2.6 million ha, South America, especially emerging nations, is the second area behind Africa with the largest rate of soil loss (Bruera & Ignacio, 2021).

With a rate of 39.4% during the previous 26 years and an annual loss of 60,000–200,000 ha of native forests, Ecuador presents a serious issue in terms of deforestation (Mora et al., 2016). Between 1990 and 2018, the province of Manabí, which has the ninth-highest rate of deforestation in the nation, lost 26% of its forest cover (González, 2020). One of the main reasons for deforestation in the area is the growth of dragon fruit production, a traditional agricultural practice requiring extensive maintenance (Chalán, 2019; Ruiz, 2022).

Currently, geospatial tools provide a dynamic view of vegetation cover (Montilla et al., 2017). These tools enable the creation of satellite images for multitemporal monitoring as well as the analysis of landscape fragmentation and its effects on biodiversity through temporal and spatial simulations. In the light of this, the study's goal was to examine how Dragon fruit (*Hylocereus* sp. and *Selenicereus* sp.) cultivation converted xeric forests between 2016 and 2021.

2. Methodology

2.1 Study area

The study was carried out at El Cerezo location, which is situated in the Ecuadorian province of Manabí between the cantons of Portoviejo and Rocafuerte. This region, located between 0° 55' 37.1' S and 80° 31' 16.9' W, is a component of the xeric forest, a delicate and distinctive ecosystem that supports a high level of biodiversity. This kind of woodland is found in a dry area with 300–800 mm of annual rainfall and 25 °C typical temperatures. The study area is 1,136.56 ha, of which 86.09 ha are dragon fruit crops, 382.35 ha are regions intended for new crops, and 668.12 ha are dry forest. The study area was delineated by supervised classification of satellite photos in 2021.

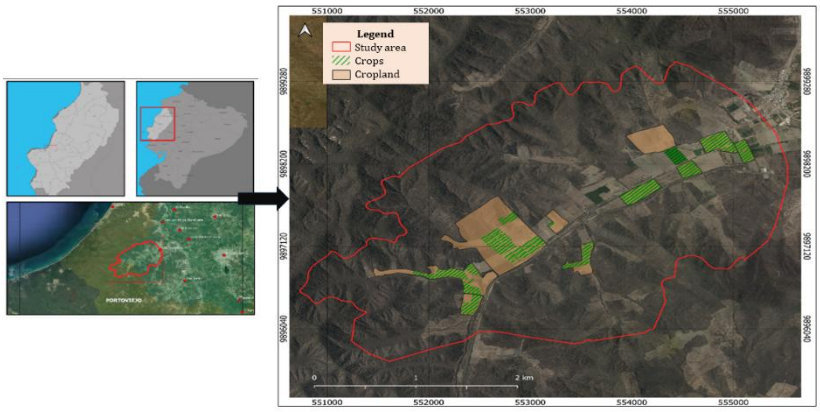

Figure 1. Location of the study area.

2.2 Crop georeferencing

During a field visit, the dragon fruit crops were georeferenced using a Garmin GPS. Following acquisition of the data, ArcGIS Pro version 2.8.4[1] was used to analyze it and produce the polygons representing the plantations that were the subject of the study. The years 2016, 2017, 2018, 2019, 2020, and 2021 were represented by the Landsat TM (Thematic Mapper), ETM+ (Enhanced Thematic Mapper), and Sentinel-2 pictures with a spatial resolution of 30x30 m and 10x10 m. These photos were acquired by using the ESPA ordering interface on the United States Geological Survey portal (USGS, 2020). However, satellite photos with less cloud cover were obtained, and the months with the least cloud cover were chosen in order to prevent data gaps caused by cloud cover (Sandoval et al., 2021).

2.3 Determination of land use change

For Landsat-8 and Sentinel-2, an RGB band composition of 6-5-2 and 11-8-2, respectively, was utilized to detect changes in land use (Rosales & Apaza, 2022). Using ArcGIS Pro's maximum likelihood technique, the satellite photos were categorized (Rufin et al., 2021). Forests, agricultural land (dragon fruit crops), crops, water features, and inhabited centers were the recognized land use types (Poveda et al., 2022). In order to detect changes in land use, the classed photos from 2016 and 2021 were finally compared.

2.4 Multi-temporal analysis and calculation of land use evolution

The categorized photos from two separate periods were compared as part of the multitemporal analysis procedure. To compute gains, coverage changes, and losses, a transition matrix (cross tabulation) was used (Reyna et al., 2017; Torres et al., 2016). The numbers that are diagonal indicate that there has been no change in coverage, whereas the values that are off-diagonal indicate a shift in coverage. The intersection tool was used in ArcGIS Pro version 2.8.4 software to do the study in accordance with Paula et al. (2018)'s approach. The average annual deforestation was calculated using equation (1) from the methodological sheet of Puyravaud (2003).

$$R = \frac{A_1 - A_2}{t_1 - t_2} \qquad (1)$$

[1] Available at https://pro.arcgis.com/es/pro-app/latest/get-started/download-arcgis-pro.htm

Where:

R: Average annual total deforestation for a given period

A1: Initial forest area (ha)

A2: Final forest area (ha)

t1: Initial year

t2: Final year

The deforestation rate and the percentage of change for each period were obtained using equation (2):

$$q = \left(\frac{A_2}{A_1}\right)^{1/(t_1 - t_2)} - 1 \qquad (2)$$

Where:

q: Deforestation rate in continental Ecuador (%)

A1: Initial forest area (ha)

A2: Final forest area (ha)

t1: Initial year

t2: Final year

2.5 Analysis of the evolution of land use change for the estimation of deforestation by 2050

Future changes in land use were modelled with consideration for the cover of vegetation. According to Soares et al. (2022), the procedure was grounded on the examination of trends, temporal and geographical phenomena, and transformation processes. Dinamica EGO software version 6[2] was utilized for this purpose, condensing the data into raster format (Pérez et al., 2020). Dinamica EGO is based on cellular automata algorithms and the evidence weights of various biophysical and socioeconomic variables identified as direct causes (Leija et al., 2021).

[2] Available at https://csr.ufmg.br/dinamica/

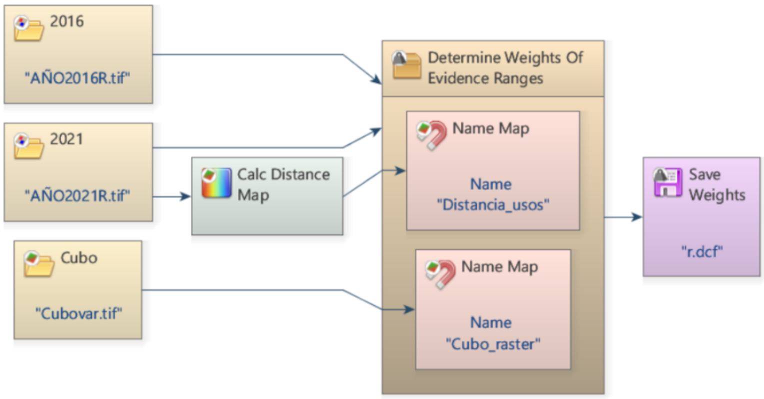

Figure 2. Categorizing variables and calculating evidence weight coefficients.

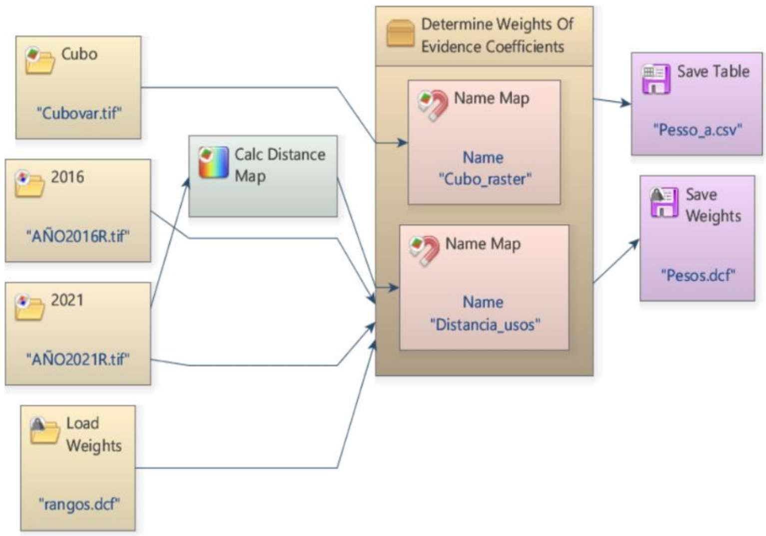

Figure 3. Evidence weight coefficient calculation.

After calculating the ranges, a model constructed in the Dinamica EGO program was used to establish the evidence coefficients (figure 3). Reyna et al. (2017) claim that the program performs a very intricate calculating method. Nonetheless, coefficients with values of 0 or negative values have no discernible effect, and the independence of the variables is a crucial need. Therefore, the independence between these variables was determined using the Cramer coefficient.

The produced findings, as shown in figure 4, will make up the projection calculation model.

Insert **Figure 4**. Projection calculation model.

In order to calculate spatial overlap at various tolerance levels, simulated and real land use change maps were compared using fuzzy similarity indices as part of the validation process (figure 5). There were two attenuation functions used in the model testing. According to what is indicated by (Rodríguez et al., 2023), the first test was conducted with the default window size of 11 pixels (330 m x 330 mq). The second test was conducted with a single pixel size of 30 x 30 m or 900 mq) increased by 15 pixels.

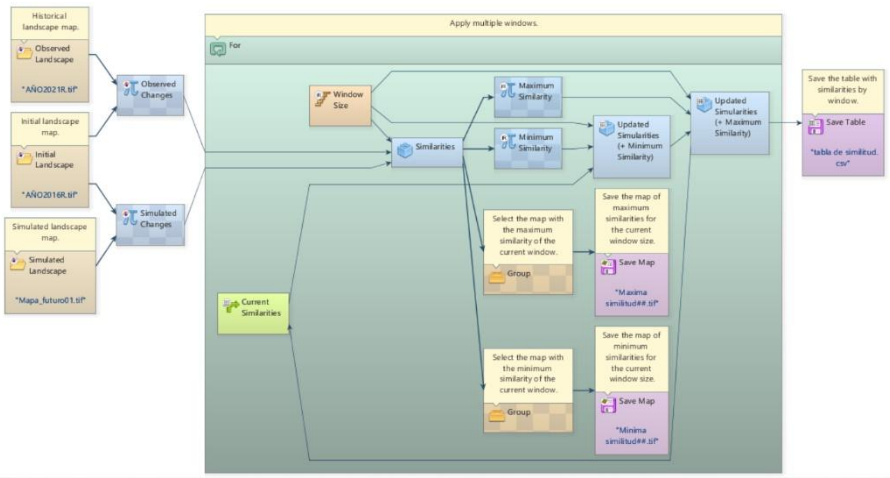

Figure 5. Prediction model validation.

3. Results and discussion

Figure 6 illustrates the change in land use from 2016 to 2021, indicating the deforestation of 245.3 ha of forest over this time. In addition, a 30.63 ha revegetation occurred in line with the rise of dragon fruit crops. There was a 41.19 ha transition to agricultural land, compared to 805.09 ha of unaltered land.

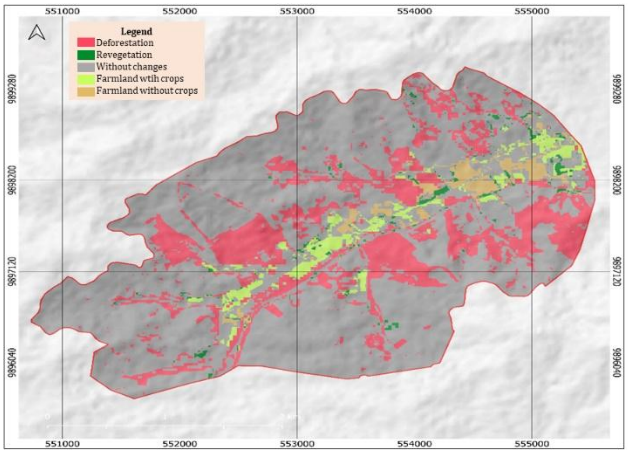

Figure 6. Land cover changes, 2016 – 2021.

Deforestation, which is mostly caused by agricultural growth, is a serious environmental problem. A number of issues, such as a lack of incentives for conservation, the growing demand for agricultural goods, and the need to increase their economic income, force communities living in or close to forest regions to convert their forests into agricultural land (World Bank, 2007). In Ecuador, deforestation is a serious problem. Estimations by Ministerio del Ambiente, Agua y Transición Ecológica de Ecuador (MAATE), the country's forest cover, which was 52% in 2009 (or around 13 million ha), decreased to 12.5 million ha by 2018, indicating an average annual net deforestation of 94,353 ha.

Between 1999 and 2018, the area of Ecuador's deforestation induced by the country's agricultural frontier expanded by 42%. In areas of one ha or less, deforestation grew by 14% between 2016 and 2018, 40% in regions of five ha and in bigger properties (areas between 20 and 50 ha), and over 80% in areas between ten and 100 ha. This growth in deforestation is regarded as a small to medium-sized deforestation agent. It is important to remember that the participation of agricultural producers, more especially, family nuclei cause the loss of forests when they move from rural to urban regions (Sierra et al., 2021).

The xeric forest in the study region is in danger of being completely destroyed due to the unchecked spread of dragon fruit, which has grown exponentially from 850 ha in 2018 to over 2,300 ha in 2022 and is predicted to reach 10,000 ha by 2025 (MAG, 2022). According to Rodríguez et al. (2021), the conversion of forests to agriculture has detrimental effects on the ecosystem, including deforestation, habitat loss, and soil degradation (FAO, 2020; Ruiz, 2022). If this monoculture is not properly maintained, it has the potential to destroy a rare and delicate environment.

The deforestation rate in the study region increased steadily between 2016 and 2020, peaking in 2019 and 2020, as seen in table 1. After that year, there is a noticeable decline, but it is still higher than the average annual deforestation rate for the years 2016–2021, which is 52,575 ha at a rate of -0.721% (keep in mind that negative numbers denote a drop in forest cover).

Table 1. Evolution of deforestation and its rate of change.

Period	Average annual deforestation (ha)	Deforestation rate %
2016-2017	31.909	-0.034
2017-2018	44.046	-0.049
2018-2019	61.336	-0.072
2019-2020	87.755	-0.111
2020-2021	37.827	-0.054
2016-2021	52.575	-0.721

Ecuador has seen a startling loss in forest cover despite having a rich biodiversity, mostly as a result of increased agricultural production. According to FAO (2020), the nation has lost a significant portion of its forest cover, with the greatest deforestation rate in South America of 1.8%, or 198 000 ha annually. Land use changes, particularly the conversion of forests into farmland, are linked to this deforestation (Loon et al., 2019). This tendency is supported by studies like those conducted in Morona Santiago by Yunda (2018) and Pastaza and Orellana by

Quezada et al. (2022), where the increase of agriculture and livestock is responsible for deforestation rates of 1% and -4.095%, respectively. The MAATE study indicates a marginal decline in the rate of deforestation from 1990 to 2016 (-0.71% and -0.66%), between 2014 and 2016, the situation worsened, with 94 353 ha of forests lost annually. Ecuador's biodiversity and ecosystems are at risk due to deforestation, which is mostly caused by the country's expanding livestock and agricultural industries. Urgent action is needed to stop this deforestation and reverse its effects.

The ecosystem and biodiversity of the Manabí province are being threatened by deforestation. Research like that conducted by Intriago & Roldán (2017) reveals concerning patterns in the Flavio Alfaro canton, where the growth of agriculture has been primarily responsible for a 29 ha (-0.01%) decline in forest cover throughout the assessed period. Similarly, Poaquiza (2023) finds that 122.88 ha of forest have been converted to agricultural land, representing an annual deforestation rate of 0.48% (16.38 ha/year) in the Pacoche Coastal Marine Wildlife Sanctuary. These findings emphasize how critical it is to go into action swiftly to halt deforestation and save the delicate ecosystems of Manabí.

It is imperative to underscore that deforestation in Manabí is intimately linked to natural elements like altitude, in addition to socioeconomic issues like agricultural growth. This link is shown in figure 7, where the distances of crops and agricultural land are represented by estimated evidence weights, which show a considerable proximity impact at a distance of no more than 100 m (X axis). The coefficients' representation is shown on the Y axis; values greater than 0 signify a larger transition from forest to agricultural land. The computed evidence weights for the distances of crops and agricultural land show a strong proximity impact at a distance of no more than 100 m, which is consistent with Osorio et al. (2015).

The research region has maximum altitudes of 280 meters above sea level (m.a.s.l.) and minimum elevations of 15 m.a.s.l., with slopes reaching up to 15%, in relation to the altitude variable. The weights of evidence determined for distances from crops and agricultural land revealed an effect of altitude at a distance of greater than 103 m, as shown on the X axis, while the Y axis depicts the coefficients in the transition from forest to agricultural soils. These statistics support Vallejo & Medinas's (2020) findings, which indicate that deforestation is more prevalent in regions with slopes of less than 20% and elevations of less than 300 m.a.s.l. It is necessary to comprehend these spatial linkages in order to put focused conservation efforts into action. Protecting places with lower elevations and slopes, where deforestation is more likely, must be given priority.

This geographical correlation demonstrates that Manabí's deforestation is focused in lower-lying areas where farming is more feasible. This aligns with the results of earlier research conducted in the area (Intriago & Roldán, 2017; Poaquiza, 2023), which emphasize that one of the primary causes of deforestation is agricultural expansion.

Figure 7. Probability of occurrence in the coverage change according to altitude.

The research area's distance to the river does not seem to be a decisive factor in deforestation. Values less than 1400 m, the closest distance to the river, have a value of 0, according to the computed evidence weights (figure 8), indicating that the distance to the river has no effect on the deforestation process. This observation is at odds with the results of Burkhardt & Scheurer (2007), who discovered that rivers that are located within 1000 m of agricultural regions contribute to deforestation by acting as sources of irrigation. In this instance, the availability of alternative irrigation water sources, like wells or rainwater collection systems, may account for the absence of association observed between the distance to the river and deforestation.

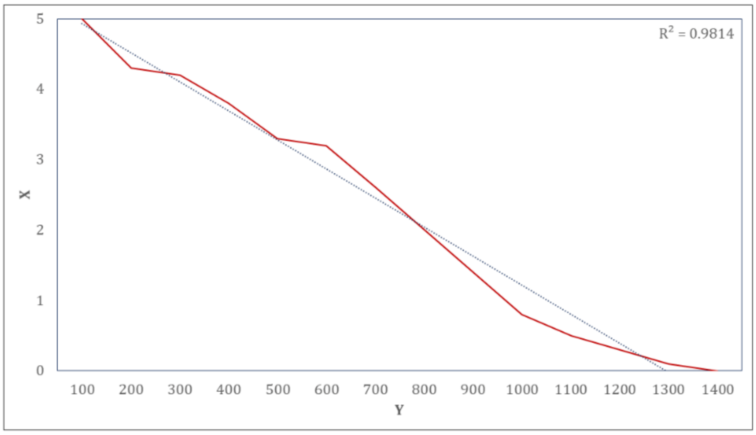

Figure 8. Probability of land cover changes according to variable distance to river.

In accordance to the aim of the study, noteworthy associations were discovered between the growth of dragon fruit farming and alterations in the land cover within the investigated region. The strongest significant connections with dragon fruit expansion are shown in table 2 between shifts from agricultural land to crops (0.4061) and from forest to agricultural land (0.6038), suggesting that these regions are more likely to be converted for this crop. These findings are in line with earlier studies by Pérez (2021); Leija et al. (2021), which show that substantial relationships are indicated by Cramer coefficients more than 0.15 and correlation values near to 1. The strong relationship seen in this instance between changes in land cover and the growth of dragon fruit implies that xeric forest degradation plays a significant role in the dynamics of this crop.

The reliability of the findings and their potential for forecasting future scenarios are supported by the geographical concordance of the computed indexes. In the same way, Caita & Castañeda (2021) draw attention to the fact that the evidence weight coefficients make it possible to determine which factors have the most effects on the system. The spread of dragon fruit farming is determined by the destruction of xeric forest, as confirmed by the greatest values of these coefficients for land cover changes in this study.

Table 2. Cramer index, transition of uses.

From	To	Cramer
Forest	Farmland	0.603841259
Forest	Crops	0.406062732
Farmland	Forest	0.0703216461
Farmland	Crops	0.700444591
Crops	Forest	0.092835845
Crops	Farmland	0.712496523

A pattern in the simulated and actual coverage at various distances is described by the data in table 3. The highest similarity is 0.9283 and the minimum is 0.8185 at a distance of 30x30 m. But as the scale goes up, the similarity goes up a lot, reaching a minimum of 0.9358 and a maximum of 0.9926, suggesting that the simulated and observed data at this size match quite a little.

Table 3. Similarity index.

Cell size (ha)	Minimal similarity	Maximum similarity
30	0.8185	0.9283
60	0.8585	0.9627
90	0.8876	0.9776
120	0.9084	0.9850
150	0.9239	0.9899
180	0.9358	0.9926

These results are closely tied to the growth of dragon fruit cultivation in xeric forests and align with the findings of Ore et al. (2021), who report that the high similarity shows that the applied simulation model is successful in capturing particular vegetation cover characteristics. These findings are crucial to comprehending the growth of dragon fruit cultivation in xeric forests. Notably, the results align with those of Espinoza (2016), who similarly assessed the degree of similarity between simulated and actual data about crop development in an urban forest area, yielding scores ranging from 0.50 to 0.90. According to his research, these data showed a good fit for the model, supporting the robustness of the findings and indicating that the model used in this study is effective at capturing the dynamics of changes in the xeric forest's vegetation cover and, consequently, the growth of dragon fruit crops in the studied area.

Since the results centre on the growth of dragon fruit agriculture in xeric woods, the comparison of the actual and simulated vegetation cover in the research region is highly important. There is a significant degree of agreement between the simulation and the actual vegetation cover in the research region, as the data show that as the cell size grows in ha, so does the resemblance between the data.

It is clear from the study region that the simulation can accurately capture the features of the xeric forest cover at a greater scale. A closer look at figure 9 reveals that the similarity between the simulated and observed cover is $R^2 = 0.9662$. This suggests that there is a significant correlation between the simulated and observed data on the expansion of dragon fruit agriculture in the research area.

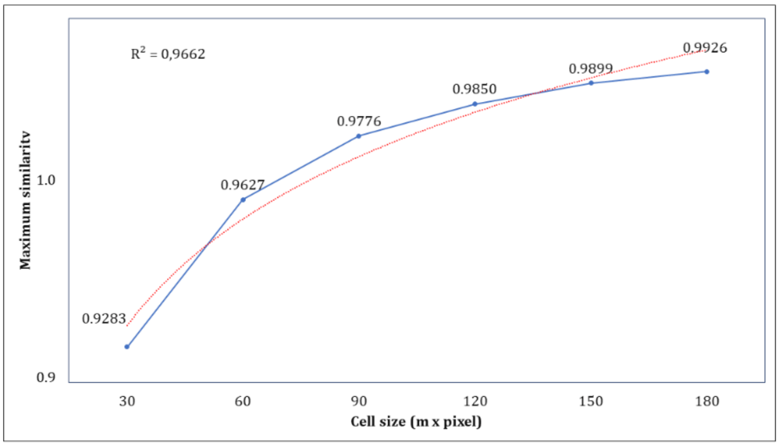

Figure 9. Validation with constant decay function.

For environmental planning and decision-making in the research area, these findings are very relevant. According to them, the models used to depict vegetation cover dynamics in the xeric forest and, therefore, in the growth of dragon fruit farming, can be more accurate and dependable when used to a larger scale. In the particular context of a xeric forest, this is crucial for the protection of this unique ecosystem, sustainable natural resource management, and the successful use of mitigation techniques against climate change.

Figure 10 shows how the land cover in the study region is expected to change in 2050. This figure's data reflect a prediction that helps us comprehend how dragon fruit production affects the xeric forest. A total of 156,874 ha of forest cover, 685,861 ha of agricultural land and 293,634 ha of dragon fruit cultivation are predicted by 2050. Figure 11 details the modifications and development of the 2016–2050 future forecast.

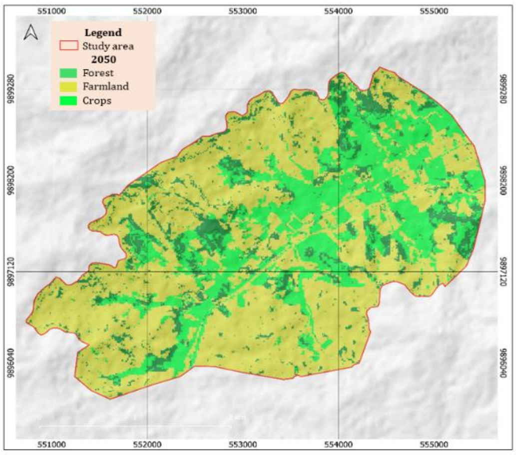

Figure 10. Coverage projection for 2050.

The projection for the year 2050, as illustrated in figure 10, indicates that agricultural land will increase by 685 ha, indicating a 79% increase; dragon fruit cultivation will increase to 293.63 ha; and forest cover will decrease to 156,874 ha, corresponding to a 77% reduction with a deforestation rate of 0.85%, losing a total of 511.24 ha. It's critical to remember that, as a forecast, the model is prone to uncertainty and might be impacted by unanticipated developments like shifting land use regulations or fluctuations in the climate. According to Torrella et al. (2018), there is a degree of uncertainty regarding the exact occurrence of deforestation due to the predictive nature of models. However, it is imperative to take into account the primary drivers of this process when devising strategies for managing forest resources and mitigating its effects. This observation is consistent with their findings.

Sierra et al. (2021) conducted a study on deforestation in Ecuador from 1990 to 2018. The study covered a research area of approximately 5,272.36 square kilometres, or 2.1% of Ecuador's continental territory, and included the Cordillera and Plains of the Central Pacific. This analysis came to the conclusion that there is a 0.9, or crucial, likelihood of changes in the area by 2030.

Consistent with what has been said thus far, Villarreal & Arteaga (2019) attribute these changes to the way agriculture affects the forest cover and speculate that the demand for resources may make matters worse. A substantial likelihood of a decrease in forest cover is associated with the development of agricultural activities and the research area's boundaries, as per the 2050 deforestation prediction model.

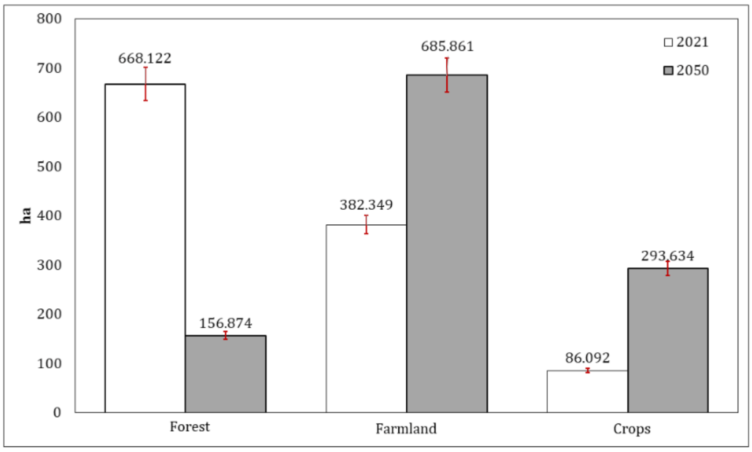

Figure 11. Changes in coverage projection 2021-2050.

4. Conclusions

The increased demand for dragon fruit has led to an alarming 52.57 ha of deforestation between 2016 and 2021 in Manabí due to the development of dragon fruit farming. This phenomenon has detrimental effects on the ecosystem, such as habitat loss and soil degradation, even if the pace of deforestation varies. Concerns regarding sustainability and biodiversity are raised by projections for 2050, which show an annual deforestation rate of 0.85% and an increase in dragon fruit to 293,634 ha. To lessen these consequences and make sure that agriculture and conservation are sustainably balanced in the area, it is imperative to put deforestation prevention initiatives into action, support environmental education, and encourage good agricultural practices.

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Authors

Lizardo Reyna-Bowen *(corresponding author)*
http://orcid.org/0000-0003-0352-4005
jlreyna@espam.edu.ec
Escuela Superior Politécnica Agropecuaria de Manabí Manuel Félix López, Calceta, Ecuador

Walther Antonio Cevallos Meza
Escuela Superior Politécnica Agropecuaria de Manabí Manuel Félix López, Calceta, Ecuador

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