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Fragmentation Analysis of Capisaan Surface Karst Landscape through Changes in Land Use and Land Cover using FRAGSTATS

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Abstract

Changes in land cover mainly brought by humans could alter how landscapes function, which has an impact on the variety and health of the local biota. This study examined the fragmentation shifts of the Capisaan Cave System surface landscape by looking at changes in land use and land cover using Landsat images, ArcGIS and Google Earth imageries to generate classified land covers for the years 2001, 2005, 2010, 2016 and 2019. Fragmentation was analyzed through FRAGSTATS with forest; shrubland and orchard (SO); and agriculture and clearing (AC) as class types. Results showed that the most significant change in the landscape was in the year 2010 with AC significantly increasing its area and aggregation causing other class types to exhibit more fragmentation. Forest and SO covers displayed huge losses indicated by decreased class area and average size of patches accompanied by a more subdivided landscape shown by their increased number of patches. Although forest and SO slightly recovered in the class area in 2016, values were far from recovering to 2001 values. FRAGSTATS data suggest lowering biodiversity values and paying importance to reserve size in the maintenance of species diversity. The edge effect as a result of class and landscape fragmentation in forest vegetation might have been reduced at the landscape level as indicated by the reduced fractal dimension, as well as sustaining patch cohesion and increased clumpiness. However, abatement of edge effect could be easily limited and reversed if the reduction of the total area of forest available in the landscape continues.

Keywords*:* biodiversity, fragmentation, geographic information system, land cover, land use

1. Introduction

Humans have accelerated the transformation of landscapes, proliferating fragmentation in the process which then jeopardizes ecosystem functions and services (Cai *et al.*, 2016). In karst landscapes, dissolution patterns of carbonate rocks are highly dictated by the surface land cover. Changes in land use and land cover (LULC) have a significant impact on the hydrology, geology (speleogen and speleothem) and biota of any subterranean caves that may be present (Li *et al.*, 2022).

Human-induced changes in LULC modify the structure and function of karst landscapes and derived ecosystem services which affect the diversity and well-being of creatures that depend on them (Mitchell, 2013). Forests in karst and biological diversity always mend together to produce quality ecological services for communities directly consuming them. Actions of communities to any management options for forest resources or forest-dominated landscapes are very crucial for the sustainability of services derived from them (Muttaqin *et al.*, 2019). Forests are important repositories of genetic, species and ecosystem diversity by offering diverse habitats for different plants, animals and microorganisms (Food and Agriculture Organization, 2017). Various forest types and their landscape patterns play a vital role in the daily life of rural communities in many areas. Ultimately, forests are vital to the survival and well-being of people by providing shelter, food, medicine and clean water and maintaining a stable climate and environment through carbon sequestration, flood control and protection against soil erosion and desertification (United Nations Educational, Scientific and Cultural Organization, 2010).

Fragmentation happens when a large forest is broken into smaller forest patches mainly brought by human developments. Effects of forest fragmentation, in addition to the introduction of exotic species and climate change, greatly influence forest biodiversity patterns and quantity. In many areas, isolated forest fragments and heavily modified landscapes can be observed to cause the disappearance of many plant and animal species (Liu *et al.*, 2019). Edge effects resulting from fragmenting remaining forests further diminish biodiversity leaving areas too small for some species to persist or too far apart for other species to move between affecting species richness and composition (Ewers and Didham, 2006).

It is essential in landscape management to determine and analyze accurate changes in the spatiotemporal patterns of LULC (Abdullah *et al*., 2019), especially in forest-dominated landscapes, to detect crucial trends needing immediate intervention to ensure the sustainability of important functions and services, especially of unique natural resources. Monitoring this transition offers a planning and development lens for managing sustainable karst LULC.

This study examined the landscape fragmentation shifts of the karst landscape of Barangay Capisaan, Kasibu, Nueva Vizcaya, Philippines where the Capisaan Cave System is located. Specifically, this study attempted to characterize the changes in the LULC patterns for the years 2001, 2005, 2010, 2016 and 2019 satellite images to subsequently suggest possible biodiversity implications of fragmentation changes in the Capisaan Surface Karst Landscape (CSKL).

2. Methodology

2.1 The Study Area: Capisaan Surface Karst Landscape

The CSKL (Figure 1) and its cave system have a unique biodiversity which stimulated ecotourism in the area since 1998. Its residual forest is a composition of premium tree species of the Dipterocarpaceae family, almaciga (*Agathis philippinensis*) and malapapaya (*Polyscias nodosa*) and is home to several wildlife species. Its water resource supplies the needs of the community and their agricultural farms while the cave system offers a good source of income and promotion of ecotourism.

Situated within 700-900 masl at the heart of Barangay Capisaan at Malabing Valley in Kasibu, Nueva Vizcaya, Philippines, the area holds the 4.2-km long Capisaan Cave System. It is geographically situated between 121.3779° and 121.4243° E longitudes and between 16.3035° and 16.3406° N latitudes. It has a total land area of 1,515.96 ha. To date, 11 entrance and exit points of the cave system have been discovered: *Lion*; *Sang-at Salug*; *Alayan* 1 and 2; *Malukbo* 1, 2 and 3; *Gaia*; *Heaven*; *Sabrina*; and the recently discovered *Ulap*. *Heaven* and *Sabrina* are off-limits to sightseers while *Ulap* is being surveyed for its ecotourism potential. Interestingly, seven entrances were linked by narrow passages giving more route options for cavers visiting the area (Caparas, 2011).

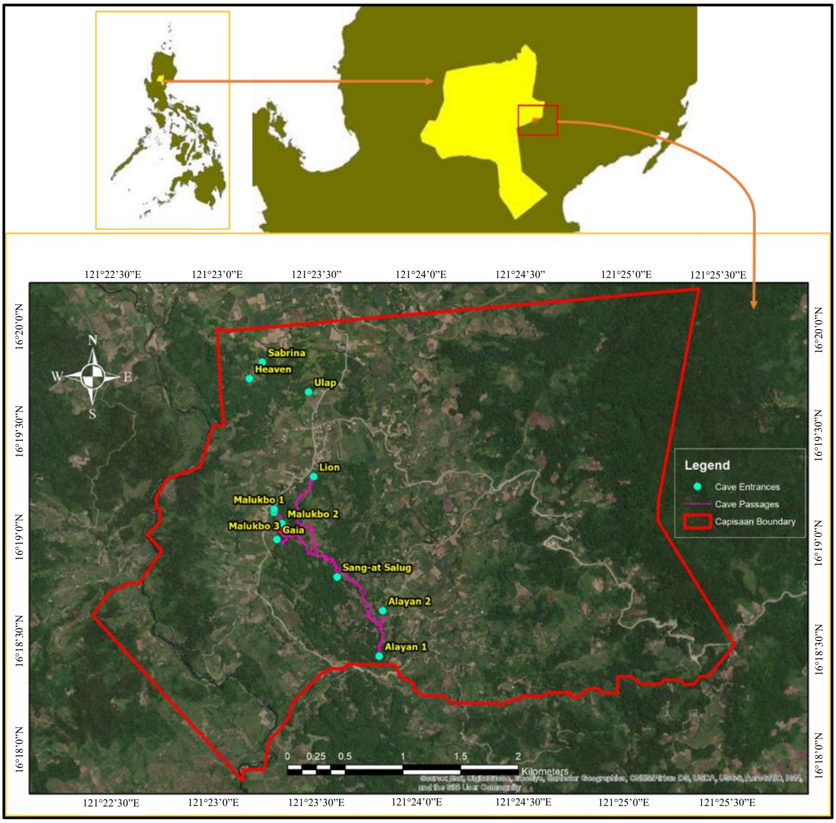

Figure 1. Map of Capisaan Cave System

2.2 Land Use and Land Cover

2.2.1 Forest

Based on available maps and ground observations, there are still patches covered with forest vegetation. This vegetation dominantly consists of dipterocarp species that are endemic in the area such as 'lauan' (*Shorea* sp.), tanguile (*Shorea polysperma*), mayapis (*Shorea palosapis*), and others. Underneath these areas are usually planted with coffee (*Coffea* sp.) by some residents of the community. Adjacent to this vegetation are existing farmlands usually planted with cash crops, betel leaf (*Piper betle*) locally known as 'hapid' and citrus (*Citrus* sp.). Elders in the community accounted that the area was previously covered by dense forest.

2.2.2 Shrublands and Orchards

These types of vegetation covers are very visible in the area, albeit scattered. The occurrence of this grasslands/brushlands type of land classification was created mainly due to fallow periods in the farming practices in the upland areas. Orchards are planted with citrus and pomelo (*Citrus maxima*) as the main fruit trees by the community. On the other hand, other fruit trees like rambutan (*Nephelium lappaceum*), 'lansones' (*Lansium domesticum*), jackfruit (*Artocarpus heterophyllus*) and banana (*Musa* sp.) are gaining popularity in the area. According to community accounts, there is a significant decrease in the number of farmers engaged recently in citrus farming because of the high price of farm inputs.

2.2.3 Agriculture and Clearings

The majority of the residents are engaged in farming activities. These farmers primarily produce rice (*Oryza sativa*), corn (*Zea mays*), coffee, ginger (*Zingiber officinale*) and cash crops. Livestock farming as an alternative livelihood of the community includes rearing of chicken (*Gallus gallus domesticus*), swine (*Sus* sp.), duck (*Anas* sp.), goat (*Capra* sp.) and tilapia (*Oreochromis niloticus*). Other cleared and open locations were those used as build-up areas. The main crops planted on the surface of the cave system were ginger and betel leaf. The betel leaves were generally planted on the rocky areas/limestone outcrops of the cave surface.

2.3 Image and Data Processing

The aid of geographic information system (GIS) techniques, high-resolution Google Earth imageries (HRGEI), remote sensing or use of satellite data and FRAGSTATS computer software program have been employed to analyze five temporal (2001-2005-2010-2016-2019) landscape patterns of CSKL.

2.4 Data Acquisition

Landsat 5 and Landsat 8 satellite image data were acquired from the website of the United States Geological Survey (USGS) (n.d.). Landsat satellite program provides a global archive of satellite photos having collections of previous and up-to-date satellite images worldwide managed and operated by the USGS. Landsat 5 and Landsat 8 were used for 2001, 2005 and 2010; and 2016 and 2019 Capisaan image data, respectively. They were used because these are free and readily available with a spectral resolution of 30 m. After careful selection, images taken on March 23, 2001, January 13, 2005 (with the cloud portion masked with image taken on May 5, 2005), February 12, 2010, February 13, 2016 and February 21, 2019 (with the cloud portion masked with an image taken on May 28, 2019) were chosen as these images were free of cloud interference over Capisaan.

2.5 Image Processing

All available bands of each Landsat data were processed into one composite image (multi-band layer) by stacking individual band images using the image analysis function of ArcMap 10.6 GIS software (Environmental Systems Research Institute, 2018). The composite image was masked to the barangay boundary of Capisaan to delimit the spatial coverage of the study area. The masked image of Capisaan was then classified according to different land uses using the image classification function of ArcMap. Among the different classification options, the Iso Cluster Unsupervised Classification was used.

Unsupervised classification uses naturally occurring statistical groupings in the data to determine the clusters into which the data would be classified. It uses all available bands in the composite image regardless of what bands are set to RGB. To normalize the band difference between Landsat 5 and Landsat 8, their seven similar bands were used in the composite image. Tables 1 and 2 show the syntax for the Iso Cluster Unsupervised Classification and the seven similar Landsat bands utilized in the classification.

Table 1. Iso Cluster Unsupervised Classification syntax utilized in the classification

Classification parameters	Inputs	Explanation
Number of classes	10	
Minimum class size	4	Smaller sample interval is used to ensure small features are not skipped and attain the desired number of classes.
Sample interval	1	Means all cells are samples.

The generated classes were evaluated using current and historical HRGEI of Capisaan to determine and validate the closeness of classification on the natural image captured by Google Earth Pro 7.0.3 (Google, 2019) and with the personal knowledge of the researchers as observed onsite. Ground truthing with geotagging was also done on February 15-22, 2019 to assure the accuracy of classification.

Table 2. Landsat bands utilized in the classification

Band name	Landsat 5	Landsat 8
Blue	Band 1	Band 2
Green	Band 2	Band 3
Red	Band 3	Band 4
Near infrared	Band 4	Band 5
Short wave infrared 1	Band 5	Band 6
Short wave infrared 2	Band 7	Band 7
TIR	Band 6	Band 10 (TIRS1) and Band 11(TIRS2)

Ten detailed LULC classes were produced which included: 1. dense natural forest; 2. secondary forest; 3. secondary forest-sparse; 4. secondary forest trees and vines; 5. shrubland; 6. orchard; 7. ricefield-cleared or water body; 8. ricefield-planted and grassland; 9. *kaingin*, clearing and 'ikmo'; and 10. agriculture, clearing and built-up. The produced classes were then reclassified according to these three class groupings: 1. forest (dense natural forest, secondary forest, secondary forest-sparse, secondary forest-trees and vines); 2. shrubland and orchard (SO) (shrubland, orchard); and 3. agriculture and clearing (AC) (ricefield-cleared and water body, ricefield-planted and grassland; *kaingin*, clearing, and 'ikmo'; agriculture, clearing and built-up). The resulting classified images are presented in Figure 2. The overall accuracy of classification was further assessed by generating the sample error matrix in ArcMap creating accuracy assessment points and comparing the actual and classified land cover of the generated image. The computed overall accuracy of the generated image was around 96%.

2.6 FRAGSTATS Analysis

FRAGSTATS version 4.2.1 (UMass Landscape Ecology Lab, 2018) is a software package designed to compute a wide variety of landscape metrics for categorical map patterns (McGarigal and Marks, 1995). This software computes statistical measures of the landscape composition at patch, class and landscape levels using landscape geotiff images as input data. For this study, landscape indices were measured at the class and landscape levels. Class indices depict the pattern and spatial distribution of a specific patch type within a landscape; whereas, landscape indices represent the spatial pattern of the entire landscape mosaic considering all patch types simultaneously. Most of the class indices could be interpreted as fragmentation indices because they measure the configuration of a particular patch type; whereas, most of the landscape indices could be interpreted more broadly as landscape heterogeneity indices because they measure the overall landscape pattern (McGarigal *et al.*, 2012). Landscape indices broadly fall into one of two categories: non-spatial and spatial. The spatial and non-spatial FRAGSTATS metrics used in the study are shown in Table 3.

Table 3. FRAGSTATS metrics selected for the analysis showing code and description

Acronym	Metric name	Description (McGarigal and Marks, 1995; McGarigal *et al.*, 2012)
CA	Total (class) area	CA is a metric for the composition of a landscape; precisely, how much of it is made up of a given kind of patch. Several of the class and landscape metrics are computed using the class area in addition to its direct interpretative value. As the patch type disappears from the landscape, CA gets closer to zero. When the entire landscape is made up of a single patch type, CA = total area. Total CA is equal to the sum of all patch areas (m^2) of the relevant patch type divided by 10,000 (equivalent to hectares).
NP	Number of patches	It quantifies the number of patches of a particular class type and reflects the composition of the area. As a fragmentation index, it can be used to determine the degree of class-level fragmentation. In general, greater NP indicates greater spatial variability. The number of patches of the respective patch type is represented by NP (class).
AREA_MN	Mean patch size	The function of the entire class area and the number of patches in the class; it does not, however, specify the quantity of patches present and is measured in hectares (ha). In connection to CA, patch density (PD) and patch size variability, mean patch size can be used as an indicator of patch fragmentation. AREA_MN is equal to the product of all patch types' total areas (m^2) divided by the total number of patches of that kind, divided by 10,000 (equivalent to hectares).
LPI	Largest patch index	LPI quantifies the proportion of the overall landscape area made up of the largest patch at the class level. This makes it a straightforward indicator of supremacy. When the largest patch of the matching patch type gets smaller and smaller, LPI gets closer to 0. When a single patch of the relevant patch type covers the entire ground, or when the largest patch makes up 100% of the landscape, LPI = 100. LPI is calculated by dividing the overall landscape area (m^2) by the size of the largest patch of the landscape, multiplied by 100 (equivalent to a percentage).

Table 3 continued.

PAFRAC	Perimeter-area fractal dimension	PAFRAC reflects shape complexity across a range of spatial scales (patch sizes). For a two-dimensional landscape mosaic, a fractal dimension larger than 1 denotes a break from Euclidean geometry (i.e., an increase in patch shape complexity). approaches 1 for shapes with extremely straightforward perimeters, like squares and approaches 2 for shapes with complex, plane-filling perimeters. PAFRAC is calculated by dividing the logarithm of the patch area by twice the logarithm of the perimeter of the patch.
COHESION	Patch cohesion index	The physical connectivity of the appropriate patch type is quantified by COHESION. As a patch type gets more clumped or aggregated in its distribution and, consequently, more physically coupled, patch cohesiveness rises. As the percentage of the landscape made up of the focus class declines and becomes more fragmented and physically disconnected, COHESION approaches zero. COHESION is defined as 1 minus the total patch perimeter (measured in terms of the number of cell surfaces) divided by the total patch perimeter times the square root of the total patch area (measured in terms of the number of cells) for patches of the corresponding patch type, multiplied by 100 to equate it to percentage.
TCA	Total core area	The core area represents the area in the patch greater than the specified depth-of-edge distance from the perimeter. When all points within a patch are less than the given depth-of-edge distance(s) from the patch perimeters, TCA = 0. As the given depth-of-edge distance(s) gets smaller and patch forms are simpler, TCA gets closer to the entire landscape area. TCA is calculated by dividing the total core area (m^2) of each patch of the respective patch type by 10,000. (equivalent to hectares).
CLUMPY	Clumpiness	A metric computed at the class level only, with a range of -1 for the patch type when it is most disaggregated and 1 for the patch type when it is most clumped. Greater dispersion (or disaggregation) than would be predicted by a spatially random distribution is indicated by values less than zero, and greater contagion is indicated by values greater than zero. According to a geographically random distribution, CLUMPY is the proportionate divergence of the proportion of like adjacencies involving the corresponding class from what would be predicted.

Non-spatial metrics used in the study described the landscape composition which included the measurement of total class area, largest patch index (LPI) and mean patch size (MPS). Spatial indices identified attributes of patches and contain information related to fragmentation measurement. The spatial indices used in the study to describe patch composition, configuration and shape included perimeter-area fractal dimension (PAFRAC), total core area, clumpiness and patch cohesion index (PCI). The patch configuration indices calculated the degree of contact or isolation between patches (Tischendorf and Fahrig, 2000), while shape indices attempted to measure the nature of patches which may be essential for various ecological processes. Circles or squares, for example, will have less edge and potentially more core areas, while long and narrow features such as tree lines or riparian areas may have relatively small core area despite a large total area. Compact habitats may be less accessible to organisms that spread across the landscape, while curved or linear shapes may intercept more species or propagules (Rutledge, 2003).

The fractal dimension determines how complex the patch shape is. In the case of raster images, the fractal dimension ranges from one, indicating relatively simple shapes, to two, representing more complex and convoluted forms. Connectivity measures extend the concept to the entire landscape. Instead of recommending a fixed distance, the index calculates the effect of all patches within the landscape as a function of their area and distance from the focal patch; connectivity enables even small, relatively distant patches to disperse (Rutledge, 2003). Several forest species cannot and/or are reluctant to go through areas without forest cover so forest areas that are directly linked to other forest areas are more available for forest species.

The five classified temporal landscape geotiff images of Capisaan generated in ArcMap were loaded into FRAGSTATS v.4.2.1 as input layers. The “class descriptor” file used followed the final three class groupings, namely forest, SO and AC. The analysis parameter was set to “8 cell neighborhood rule” and “no sampling” for the sampling strategy.

3. Results and Discussion

The generated LULC classes of Capisaan and the result of the FRAGSTATS analysis for the five different time periods are presented in Figures 2-6 and Table 4.

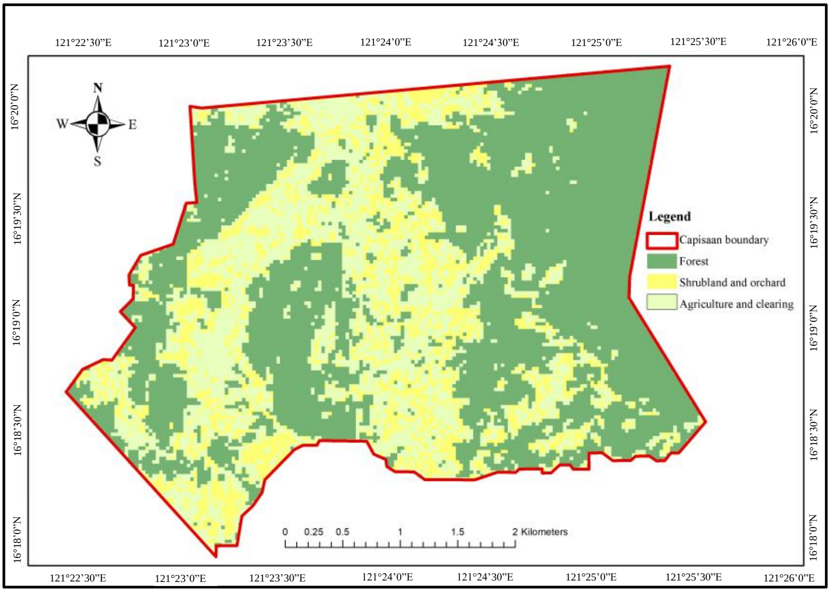

Figure 2. LULC of Capisaan in 2001

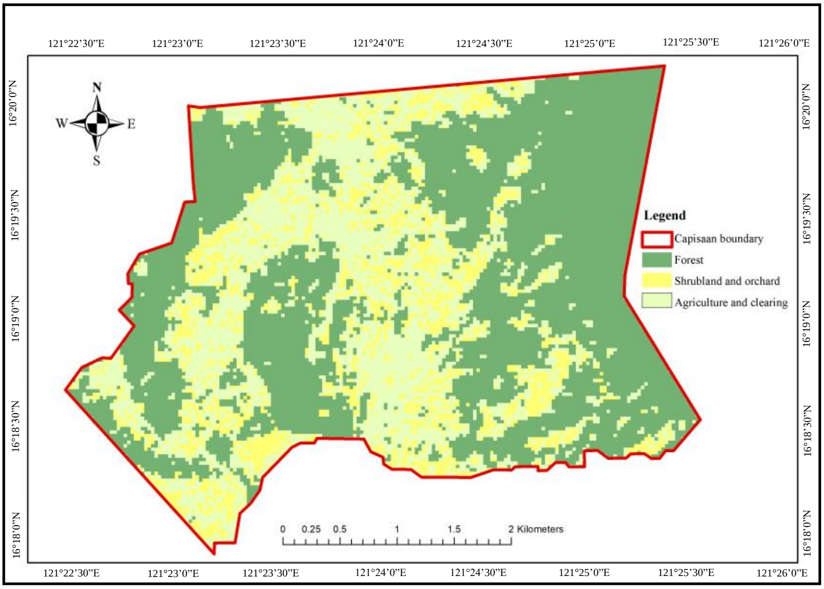

Figure 3. LULC of Capisaan in 2005

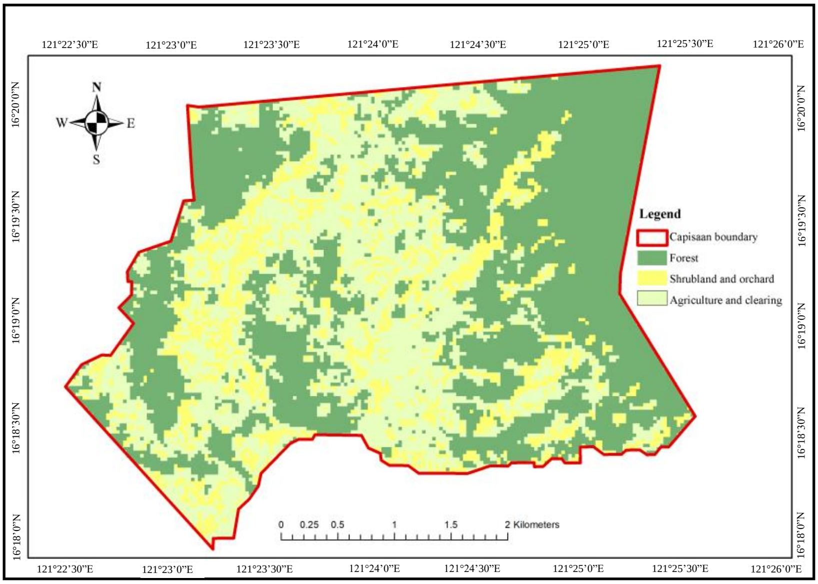

Figure 4. LULC of Capisaan in 2010

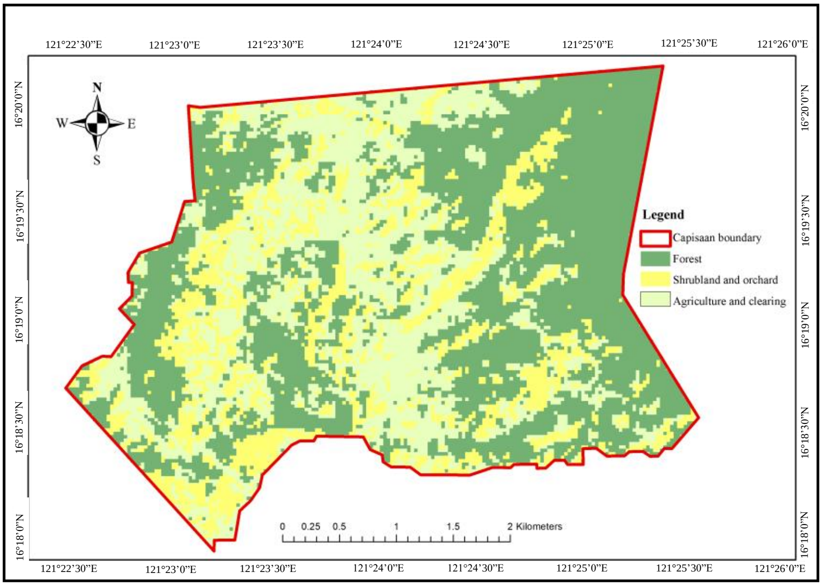

Figure 5. LULC of Capisaan in 2016

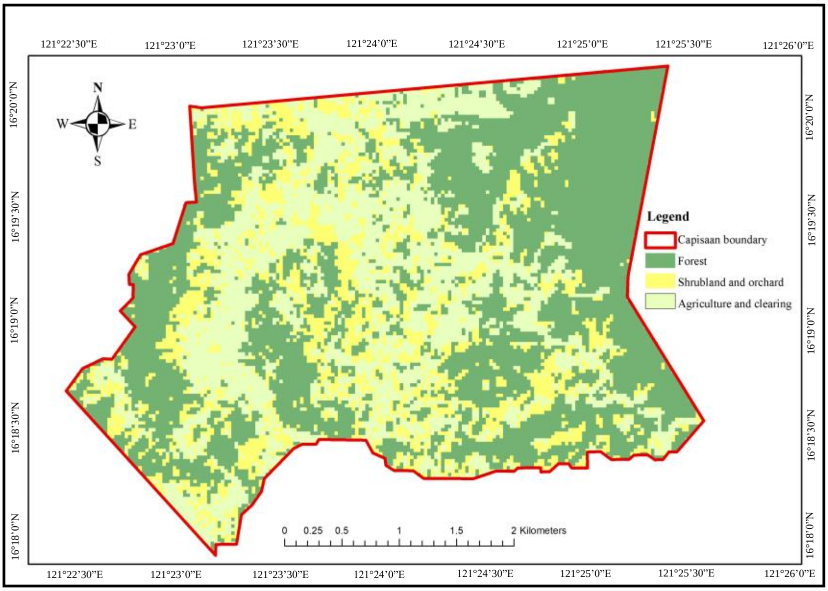

Figure 6. LULC of Capisaan in 2019

Table 4. CSKL FRAGSTAT metrics change from 2001, 2005, 2010, 2016 and 2019

Year	Type	CA (ha)	LPI (%)	AREA_ MN (ha)	PAFRA C	TCA (ha)	CLUMPY	COHESION
2001	Forest	823.50	33.96	9.80	1.41	577.8	0.76	98.54
2001	SO	259.38	2.02	0.90	1.61	23.76	0.39	87.02
2001	AC	424.89	18.84	1.99	1.63	79.83	0.43	97.77
2005	Forest	815.58	32.59	8.59	1.41	575.82	0.77	98.53
2005	SO	243.09	0.89	0.74	1.59	22.14	0.38	81.39
2005	AC	449.10	23.49	2.21	1.63	99.9	0.47	98.44
2010	Forest	737.37	28.07	7.02	1.42	482.67	0.74	97.94
2010	SO	247.86	3.13	0.87	1.55	27.54	0.44	87.50
2010	AC	522.54	24.14	3.63	1.57	143.28	0.51	98.41
2016	Forest	723.15	30.01	5.09	1.44	436.5	0.70	98.13
2016	SO	318.24	2.95	1.17	1.50	67.05	0.52	88.55
2016	AC	466.38	18.58	2.32	1.56	136.35	0.53	97.49
2019	Forest	740.43	25.14	4.28	1.49	419.67	0.65	97.71
2019	SO	305.91	2.22	0.74	1.53	37.08	0.40	84.13
2019	AC	461.43	21.33	2.47	1.50	148.86	0.58	97.92

SO – shrubland and orchard; AC – agriculture and clearing

3.1 Class Area

The forest cover of Capisaan gradually reduced from 823.50 ha in 2001 to 740.43 ha in 2019 (Figure 7); a total loss of 83.07 ha was converted to other land uses and covers. The biggest decline happened between 2005 to 2010 where 78.21 ha were lost and did not recover until 2016. Interestingly, it bounced back a little from 2016 to the present gaining 17.28 ha. On the other hand, conversion to agricultural production and more clearings have been progressive from 2001 to 2010 and then declined in later years to the present. Subsequently, SO gained more areas from 2010 to 2016. Overall, 48.84-54.32% of the CSKL was covered with forest, 16.03-20.99% was categorized as SO, and 28.03-34.47% falls under AC as observed within the study period. In general, FRAGSTATS analysis showed a reduction of 10.09% of the total forest cover with reference to the original forest cover in the year 2001, while AC including built-up increased by 8.60% from 2001 to 2019.

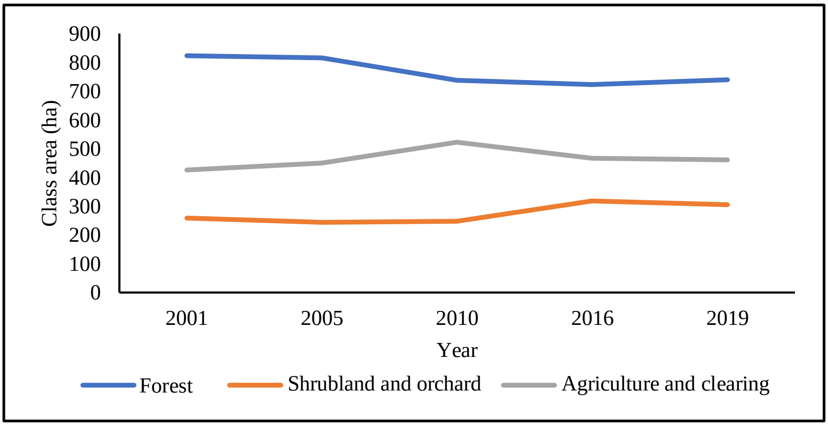

Figure 7. Change in the total class area from 2001 to 2019 of Capisaan LULC

The trend illustrated by the above figure can be attributed to the change in government attention to the Capisaan landscape. Enforcement of forestry laws and regulations was affected by the amount of attention given by political figures to this site. Based on community accounts, the years when less attention was given to this site were also the years when most deforestation, *kaingin*, expansion of orchards and conversion to agriculture were rampant due to the lenient implementation of forestry laws and regulations. Heightened promotion of the site as a major tourism destination in recent years has provided a stricter implementation of forestry laws and better forest protection programs that have allowed the forest cover to change course and recover a little.

3.2 Largest Patch Index

Proportions of the LPI of all three classes were consistent with their total class area measurements (Figure 8). The largest patch index of forest cover, however, decreased throughout the assessment years: from 33.95% in 2001 to 25.14% in 2019. The gain of LPI for AC from 2001 to 2010 was consistent with the losses in forest LPI – an indication of more *kaingin* areas opened and further expansion of AC along forest edges. The LPI of SO remained the smallest and most consistent throughout the years. The LPI of the forest declined by 25.95% from 511.89 ha in 2001 to 379.05 ha in 2019.

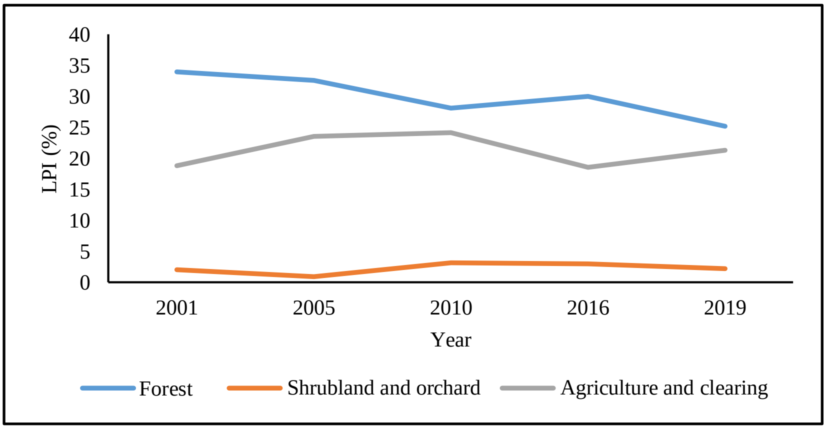

Figure 8. Change in LPI from 2001 to 2019 of Capisaan LULC

3.3 Mean Patch Size

As more patches were created, the MPS became smaller especially if the variation of individual patch areas is huge. Smaller patches of the same class tend to reduce the MPS to a smaller value. The existence of smaller forest patches significantly reduced its MPS from 9.80 ha in 2001 to 4.28 ha in 2019 (Figure 9), an indication of getting more fragmented conditions. Agriculture and clearing had a perceptible increase from 2005 (2.21 ha) to 2010 (3.63 ha), which then returned near to its baseline MPS in 2016 up to the present; SO remained almost constant. This trend could be explained by the same reasons affecting the changes in the total class area metric for Capisaan.

3.4 Perimeter-Area Fractal Dimension

The forest class type had the smallest PFRAC (1.41-1.49) with an increasing record from 2001 to 2019, while SO (1.61-1.50) and AC (1.63-1.50) had both higher values with a decreasing trend (Figure 10). While forest patches became more complex in shape due to pressures of expanding AC, patches of SO and AC became simpler in shape. It was also visible that from 2016 to 2019, AC increased in shape complexity, which may be due to expanding clearings for other land uses (e.g., built-up, road widening and expanding betel leaf plantations).

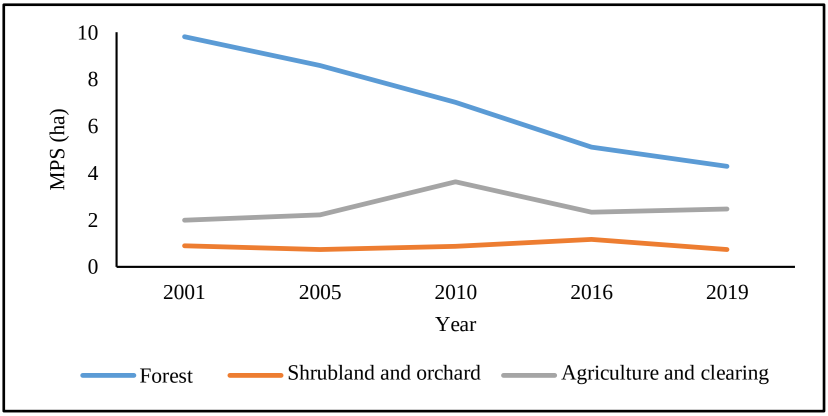

Figure 9. Change in MPS from 2001 to 2019 of Capisaan LULC

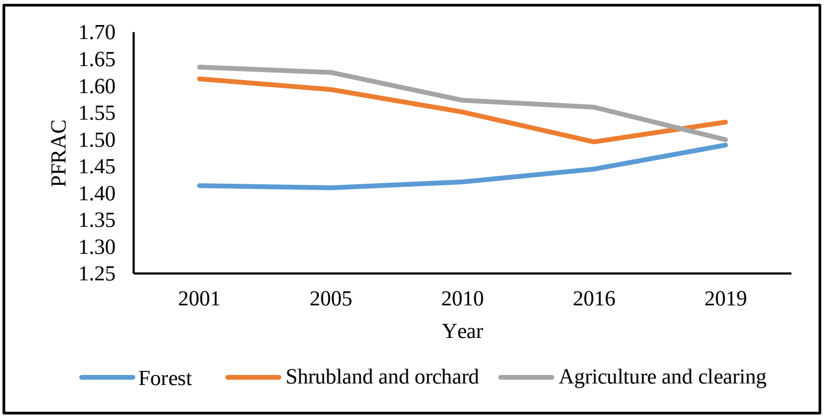

Figure 10. Change in PFRAC from 2001 to 2019 of Capisaan LULC

3.5 Total Core Area

The core area was determined as the area in the patch inside a 30-m distance from the perimeter of the patch edge. Consistent with the measurement of total patch area for all classes, forest cover registered the highest core area but in a decreasing trend from 2001 (577 ha) to 2019 (419.67 ha) (Figure 11).

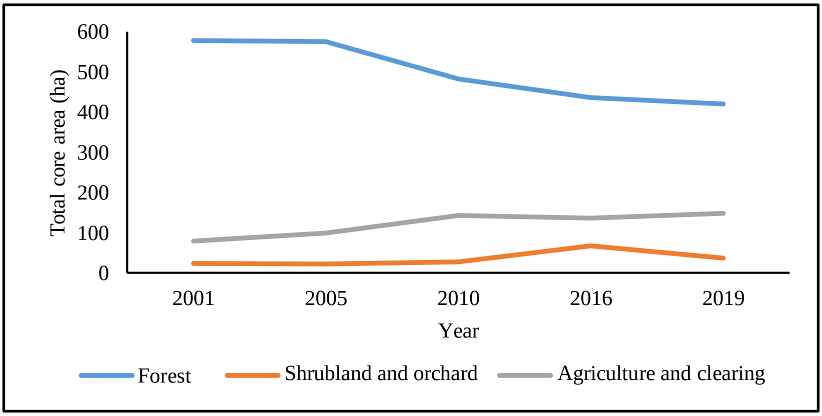

Figure 11. Change in total core area from 2001 to 2019 of Capisaan LULC

Agriculture and clearing followed with an increasing trend with 79.83 ha in 2001 to 148 ha in 2019. Shrubland and orchard remained low (23.76-27.54 ha) from 2001 to 2010 and increased to 67.06 ha in 2016 and then reduced to 37.08 ha in 2019. These trends could be closely attributed to changes in PFRAC within the different assessment years. As the shape complexity of forest patches increased, the core area decreased due to longer and more convoluted perimeters. The opposite case happened to AC where patch perimeters became simpler and resembled shapes closer to square or circle. Shrubland and orchard were the most complex in shape with a computed core area of 37.8 ha in 2019, equivalent to 12.12% of its total class area.

3.6 Clumpiness

Clumpiness readings indicate that forest patches are more closely aggregated compared with other class types. A decreasing aggregation could be viewed from 2005 to the present (Figure 12).

On the other hand, AC became clumpier from 2001 to the present. Shrubland and orchard somehow fluctuated, which may be due to the unstable and transitory LULC condition in the Capisaan landscape. The alternate fallow and conversion to agricultural crop production and betel leaf plantations contributed largely to the changes in this class type. All values were above zero indicating that all class types examined were within the threshold of greater contagion than dispersion.

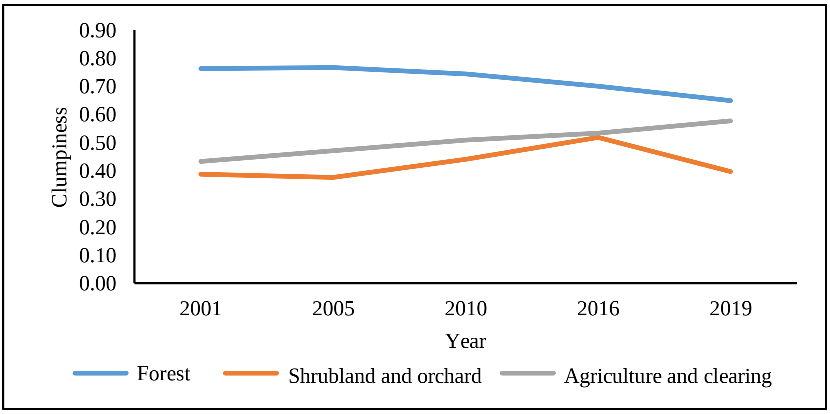

Figure 12. Change in clumpiness from 2001 to 2019 of Capisaan LULC

3.7 Patch Cohesion Index

This metric reinforces the findings of the clumpiness metric. This determines the physical connection of patches of each class type no matter what configuration they make in the entire landscape. Somehow similar to clumpiness, PCI of both forest and AC were quite high (Figure 13) indicating that at many points, the perimeter cells of similar patches had a physical connection or are adjacent to each other in the classified satellite image of Capisaan. On the other hand, patches of SO were less physically connected as indicated by its lower cohesion index.

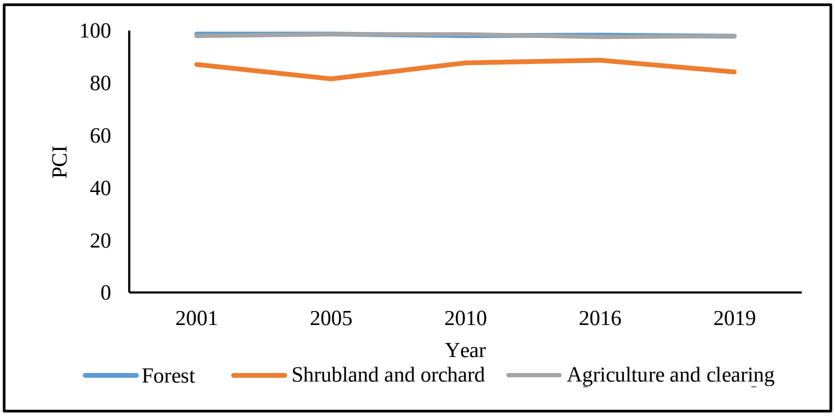

Figure 13. Change in PCI from 2001 to 2019 of Capisaan LULC

3.8 Fragmentation Analysis and Plausible Implication to Biodiversity

Survival of biological systems is improved by the existence of relatively intact "core" areas surrounded by peripheral areas which are critical for buffering the whole system against outside disturbance. In addition, these peripheral areas often benefit from "core" areas, which provide the required genetic resources necessary for maintaining higher ecosystem resilience to any disturbance (Rutledge, 2003).

FRAGSTATS result showed a significant reduction in the total class area of forest, largest patch index, MPS, total core area, and clumpiness, but an increase in the PFRAC in the CSKL from 2001 to 2019. Despite the slight increase observed in the total class area in 2019 compared with 2010 and 2016 values, the present value was still far from recovering to the 2001 value. Although direct biodiversity assessment was not covered in this study, this suite of metric trends suggests a likely inclination towards declining biodiversity values in this landscape. Island Biogeography Theory (MacArthur and Wilson, 1967) states that, ideally, bigger areas correlate to bigger reserves that can contain more species, lose species more slowly and suffer fewer effects of habitat isolation. Vastness, as associated with the area covered, can maintain larger populations, and larger populations go locally extinct less often. On the contrary, the reverse happened to the forest cover of Capisaan.

In addition, the increase of the forest's PFRAC coupled with the reduction in the total core area suggested exposure to greater edge effects or the changes to community and population structures occurring on the edge or the boundary between two different patches. Possible edge effects might include the proliferation of shade-intolerant vegetation along fragment margins, changes in microclimate and light regimes and increased wind shear. Therefore, the protection and enhancement of remaining forest core areas are highly critical to ensure the sustainability of biological systems supported by the forest. Cores are also sources of genetic resources that could sustain the diversity of ecosystems and the continuity of functions after any disturbance event.

Interestingly, there is still high patch cohesion for forest patches in the Capisaan landscape. High cohesion means better patch physical connectivity since more patches (forest covers in this case) have high chances to become more clumped and aggregated allowing more avenues for cross-boundary movements of forest species. It is worth emphasizing that forest areas that are directly connected to other forest areas are more accessible to a greater range of forest species. Metapopulation Theory (Levins, 1969) suggests that to maintain biodiversity, subpopulations particular to specific patch types must remain interconnected. Connectivity further allows for the possibility of dispersal even from small, relatively distant patches.

3.9 Land Use Changes as Cave Disturbance

Deforestation, agriculture, clearing and increased built-up areas are all surface activities that affect caves negatively (Harley *et al.*, 2011; van Beynen and Townsend, 2005). Often, these activities introduce foreign and potentially harmful chemicals into a cave. When vegetation, particularly trees, are removed from cave surfaces, sedimentation rates inside caves can increase because of the increased soil erosion, which is commonly carried by surface runoff. Agriculture can have the same effect with the addition of pesticides, herbicides and excess nutrients – all with high potential hazards on a cave system (Harley *et al.*, 2011). Urbanization affects caves by increasing pollution inside caves through stormwater runoff.

The forest fragmentation study in the area was the first to include in disturbance studies in caves. A quantitative understanding of the patterns in the area's forest loss, farming, clearing and built-up areas was obtained through analysis of the LULC changes in the surface landscape (Li *et al.*, 2022) of the Capisaan Cave System using satellite imagery, ground truthing, ArcGIS and FRAGSTATS. Changes in LULC were evident with the increase of AC including built-up overtime at the expense of forest cover. Glaringly, many parts of the karst forests in the area were cleared for plantations of *P. betle*. Although this plant could thrive under shade, growers and consumers preferred those that were under full sun. Even vertical rock walls that were difficult to access were cultivated with the crop. This was perhaps the biggest threat to the survival and conservation of forests over limestone in the study area. This result reinforces information needed in cave management by providing descriptive and quantitative data for karst surface landscape trends.

4. Conclusion and Recommendation

Landsat images and FRAGSTATS were effective and cost-efficient tools that could be used to sense different LULC types as influenced by the interplay of space and time to places of interest and could give accurate calculations for different spatial and non-spatial landscape attributes that could be utilized to detect and monitor ecological changes. Careful selection of unprocessed Landsat satellite imageries that were processed and classified by ArcGIS with proper validation through ground truthing with the aid of geotagging equipment and HRGEI were critical steps to provide useful assessments and tracking of historical and present changes in a landscape.

This research provided a qualitative and quantitative description of how LULC have changed in almost 20 years for the CSKL and provided fragmentation trends and likely implications for the dynamics of biodiversity in the area. The study period covered the time when ecotourism in the area recently started when it offered caving as the sole tourism product until it recently gained momentum as the flagship provincial tourism area. This information is timely and very important for planning and development of the area, particularly on sustainable LULC management.

Increased forest fragmentation happened in Capisaan specifically in its first decade of opening its cave resources to ecotourism. It could be inferred that previous management strategies to halt deforestation, conversion and expansion of other land uses were not so successful. However, the slight recovery of forest cover in recent years is an indication of improving forest protection and management program implementations but still should immediately address the increasing patchiness of forest cover as dissected by *kaingin* activities and expansion of betel leaf plantations. Observed signs of defragmentation could be easily reversed if the reduction of the total area of forest available in the landscape continues.

It is worth noting that attention given to develop more ecotourism projects and support in the area had somehow produced positive impacts by bringing more awareness to the community of the importance of improving forest covers and biodiversity to sustain a quality ecotourism product in the area; that is, the Capisaan Cave System. Community attitudes on the management of their local livelihoods play a vital role in the protection or destruction of important landscape patterns and attributes. It is essential that any development in the area must bring inclusive benefits to all members of the community to ensure the sustainability of projects designed to protect vital ecotourism resources.

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