MULTI-TEMPORAL ANALYSIS OF LANDSAT IMAGES FOR DEFORESTATION ASSESSMENT IN THE BOSAWAS BIOSPHERE RESERVE

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ABSTRACT

According to the latest forest assessment from the Food and Agriculture Organization of the United Nations in 2015, about 129 million hectares of forest have been loss in the past 25 years. Illegal settlements, illicit logging, and slash-and-burn farming practices are the main drivers of deforestation, especially in developing countries. The objective of this study is to assess and analyze the deforestation process in the nucleus zone of the Bosawas Biosphere Reserve, in Nicaragua, Central America, by means of remote sensing image classification and interpretation. As found out by the German International Cooperation in 2012, during the period 1987-2010 the area of loss forest corresponds to 13.6% of the total core zone. For this study, Landsat images from 2011 and 2015 were classified using both object-based and pixel-based classification approaches. Afterwards, the accuracy assessment was conducted to evaluate the performance of both methods. Finally, the net loss of total forest area was calculated by comparing the forest cover of both periods. The results of the accuracy assessment for the image of 2012 yields a Kappa coefficient of 0.89, and overall accuracy of 87% for both methods. For the image of 2015, the overall accuracy is 95%, with a Kappa value of 0.93. For the latter case, a significant improvement with respect to the pixel based method generates a Kappa of 0.84 and overall accuracy of 87%. Examination of the 2011 land cover reveals that around 6206.77 km^2 corresponded to broadleaf forest cover. This represents 86.5% of the total area analyzed. By 2015 the forest cover diminished to 5825.14 km^2, with a net forest loss equivalent to 5% of the study area. The results indicate that deforestation is an ongoing issue in the area, and that the deforestation rate has increased in the last decade.

1. INTRODUCTION

Forest gains and losses, a type of land cover change, can cause impacts on global environment through the absorption or emission of greenhouse gases and by modifying the physical properties of land surface (Foley et al., 2005). Some of most significant effects are changes in surface fluxes of radiation, heat, and moisture that can further affect the climate at different scales (Bonan, 2008). The global forest assessment conducted by the Food and Agriculture Organization (FAO) in 2015 exposed that the extent of the world's forest continues to decline as human populations continue to grow and demand for food and land increases. It also showed that South America and Africa presented the highest net annual loss of forest in 2010-2015, with 2.8 and 2 million hectares respectively. Illegal settlements, illicit logging, and slash-and-burn farming practices are the main drivers of deforestation, especially in developing nations. The Central American region is a clear example of forest degradation as a consequence of ineffective management of protected areas. Forest protection is essential to reduce the deforestation rates worldwide. This is done through legislation that includes the assessing and monitoring of forest resources.

Among all available techniques, remote sensing constitutes the most feasible and efficient way for land cover change detection. Remotely sensed imagery has increased the speed, cost efficiency, and precision of forest inventories (McRoberts and Tomppo, 2007). The integration of remote sensing and Geographical Information Systems (GIS) provides an efficient platform for data analysis, update and retrieval. The majority of land use/land cover (LULC) classifications have employed traditional pixel-based analysis. This approach consists of analyzing the spectral signature of each pixel within the image, without taking into account the contextual information (surrounding pixels). The "Salt and pepper" effect is usually present in pixel-based classification (PBC), which can reduce the classification accuracy (Campagnolo and Cerdeira, 2007). Nonetheless, in recent years an increasing trend in the use of object-based classification methods has revealed its advantages in image classification analysis (Blaschke, 2010). It has been stated that object-based image classification can achieve greater accuracy results by using both spectral and contextual information in the remotely sensed imagery (Weih and Riggan, 2010).

High-accuracy land use/land cover assessments are necessary to understand landscape patterns, changes and interactions between human and natural phenomenon. Furthermore, these landscape patterns have a strong influence on ecological processes (Turner, 1989). Human activities can cause disruption in landscape patterns, thus interfering with critical ecological processes and compromising its functional integrity. As a result, much emphasis has been placed on developing methods to quantify landscape patterns, being landscape metrics one of the most popular methods. In simple words, landscape metrics are measurements for characterizing land-use patterns, including their composition, distribution, and fragmentation (Yang et al., 2016). The purpose of this study is to assess and analyze the deforestation process in the nucleus zone of the Bosawas Biosphere Reserve, in Nicaragua, Central America, for the period 2011-2015, by combining object-based image classification and landscape ecology metrics analysis.

2. STUDY AREA

The Bosawas Biosphere Reserve is located in the north of Nicaragua, Central America. It covers portions of the largest remaining stand of tropical rain forest north of the Amazon basin (Stocks, 1994). This reserve is the southernmost portion of the Heart of the Mesoamerican Biological Corridor, which also includes other three protected areas located in Honduras: The Platano River Biosphere Reserve, the Tawahka Forest Reserve and the Patuca River National Park. The total extension of the Bosawas Biosphere Reserve is approximately 20007.6 km^2 (buffer and nucleus zone). The landscape ranges from rolling hills to steep slopes, from which flow a network of rivers, streams, and creeks, which have historically served as the only means of transportation in the area (de Jong et al., 2007).

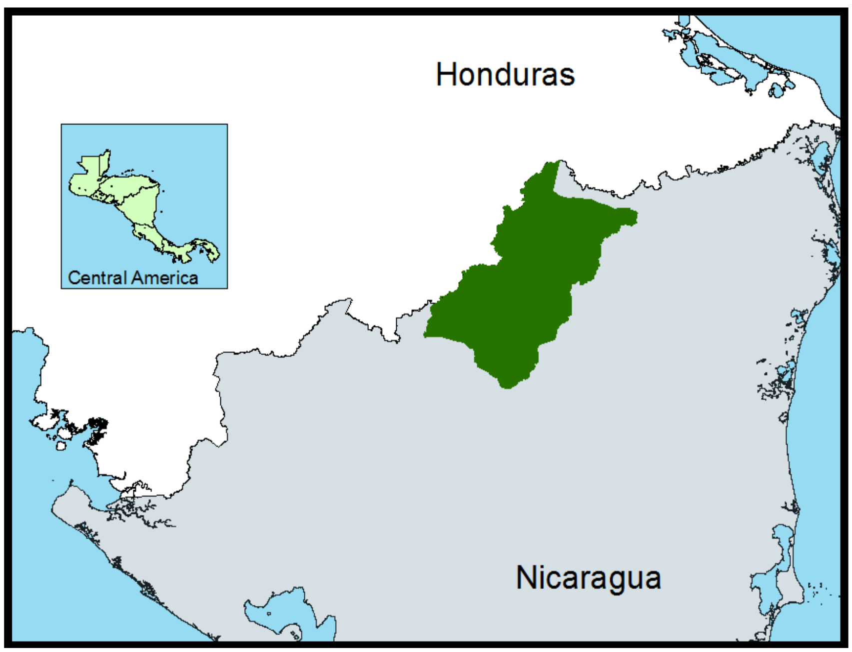

Figure 1. Location map of the Bosawas Biosphere Reserve

The core area contains the largest concentration of valuable mahogany (*Swietenia macrophylla*) remaining in Nicaragua as well as a wide diversity of rare and endangered species including jaguar (*Panthera onca*), tapir (*Tapirus bairdii*), harpy eagle (*Harpia harpyja*), among others (The Nature Conservancy, 1996). Moreover, this place is the home of some indigenous groups who live essentially from subsistence agriculture and domestic animals raising. In the last decade, there has been an increasing flux of people who have illegally settled within the biosphere reserve. The expansion of colonization, with its temporarily and unproductive agricultural systems, livestock breeding, and logging activities threatens conservation of this pristine forest ecosystem.

Although the area is under the protection of conservation laws, the lack of funds and the insufficient manpower combined with the non-existing law enforcement networks resulted in conflicts over land tenure between the illegal settlers and indigenous communities. A recent study showed that during the 1987 – 2010 period, the Bosawas Biosphere Reserve loss around 35.2 % of its forest cover, equivalent to 5647.3 km^2 (López, 2012). In that period of time, the nucleus zone loss about 970.8 km^2. The total extension of the study area is 7220.4 km^2.

3. METHODS

3.1 Data acquisition

Two Landsat images were acquired in this study. One Landsat ETM+ image corresponding to December 2011, and one Landsat OLI image from January 2015. Both images were presented low cloud contamination and were collected as surface reflectance products from the United States Geological Survey (USGS) online platform. These products were already geometric and radiometrically corrected.

3.2 Image Classification

Two different image classification approaches were taken: pixel-based and object-based. The former was conducted by selecting a set of different land cover samples across the images. Five different types of classes were defined: broadleaf forest, bare soil, water, and other types of vegetation (e.g., shrublands and grasslands). The samples were used to perform a supervised classification, employing the maximum-likelihood classifier.

On the other hand, the object-based classification (OBC) was conducted using the software eCognition Developer 9. The first step of the classification method is the segmentation process. The segmentation is a bottom-up merging technique that splits an image into unclassified "object primitives" that form the basis for the image objects and the rest of the image analysis. Since the segmentation is a trial and error process, different segmentation parameters were tried. After visual interpretation of the objects created after each segmentation, the values of scale, shape and compactness were set as follows: 25, 0.2, and 0.5, respectively. Finally, the objects were classified into the aforementioned land cover using different values of NDVI, visible brightness, and Short Wave Infrared (SWIR 1) as thresholds.

Subsequently, the accuracy assessment was performed by visually selecting 150 samples for each land cover type, and then the Kappa coefficient and Overall Accuracy were calculated. Following, the accuracy values for each method were compared to determine which approach yielded the best results.

3.3 Land cover change and deforestation patches

Afterwards, the land cover maps from 2011 and 2015 were compared to detect changes in the land cover during this period of time. Since this study is focused on changes in forest cover, the detection of deforestation patches was the main goal of this step. A deforestation patch can be defined as a closed forest region detected in a remote-sensing image and associated with a change in land cover. For this case, patches that represent a transition from forest to other types of vegetation or bare soil are considered as deforestation patches. The two types of patches were labelled as "vegetated deforestation patches" and "clear-cut patches", respectively.

3.4 Landscape Ecology Metrics (LEM) Analysis

Patch metrics from landscape ecology were used to analyze the characteristics of deforestation patches. Landscape-ecology theory proposes metrics for the geometrical and spatial properties of patches to determine the land patterns across a landscape (McGarigal, 2002). This study uses the patch metrics available in the FRAGSTATS (Spatial Pattern Analysis Program for Categorical Maps) software, which include the metrics represented in Table 1.

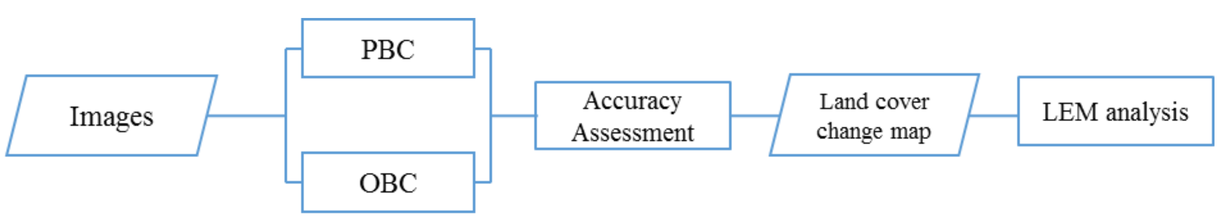

Figure 2. Workflow of the study

Table 1. Description of the patch metrics used in this study

Metrics name	Definition
Area	Area of the patch
Perimeter	Perimeter of the patch
PARA	Perimeter to area ratio, a measure of shape complexity
Shape	Adjust the PARA value for a square standard. It is the simplest measure of shape complexity. Equals 1 for square patches and >1 for more complex shapes
Frac	Fractal dimension index for measuring shape complexity. Approaches 1 for simple shapes, and approaches 2 for highly convoluted patches.
Gyrate	It is a measure of patch extensiveness or patch compaction. Can be interpreted as a measure of the average distance an organism can move across the landscape while remaining within the focal patch from a random starting point in that patch.
Circle	This metric is close to 0 for circular patches and approaches 1 for elongated, linear patches.
Contiguity	This metric analyzes the spatial connectedness of the patches (contiguity). Patches that are highly connected have a contiguity value close to one.

4. RESULTS

4.1 Accuracy assessment results

Both classification methods yielded high Overall Accuracy (OA) and Kappa coefficient values. For the pixel-based method, the classification of the Landsat TM image produced a Kappa coefficient value of 0.87, with and OA of 0.89. Furthermore, for the Landsat OLI image the Kappa value was 0.84, and OA of 0.87. The accuracy values for the OLI image were improved significantly by the object-based classification, with a Kappa coefficient and OA of 0.93 and 0.95, respectively. In the case of the Landsat TM image, the accuracy results were exactly the same (OA = 0.89; Kappa = 0.87). Due to the higher accuracy obtained through the OBC, these classification results were used in the land cover change analysis.

4.2 Classification results

Table 2 represents the classified area (and area percentage), including broadleaf forest, other type of vegetation, soil and water body. The results indicate that in 2011 about 86.5% of the analyzed area was covered by broadleaf forest. Other types of vegetation made up to 9.9% of the area. Nonetheless, by 2015, the percentage or forest area decreased to 81.2%, while the percentage covered by other types of vegetation increased to 17.2%. This indicates that within the core zone of the reserve there is an ongoing process of land cover change: the broadleaf forest area is being cleared so that the land can be used for a different purpose. The transition from forest to other types of vegetation or soil can be an indicator of human intervention in the zone, as more and more illegal settlers enter to this area to carry out livestock grazing and agriculture activities (Alvarez, 2014). Figure 3 displays the classification result for 2011 and 2015.

Table 2. Object based classification results

Classes	Year					
	2011		2015		Change	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Broadleaf forest	6206.77	86.5	5825.14	81.2	-381.63	-5.3
Other types of vegetation	710.37	9.9	1234.76	17.2	+524.39	+7.3
Soil	244.54	3.4	95.74	1.3	-148.8	-2.1
Water body	11.8	0.1	17.85	0.3	+6.05	+0.2
Total	7173.5	100	7173.5	100	-	-

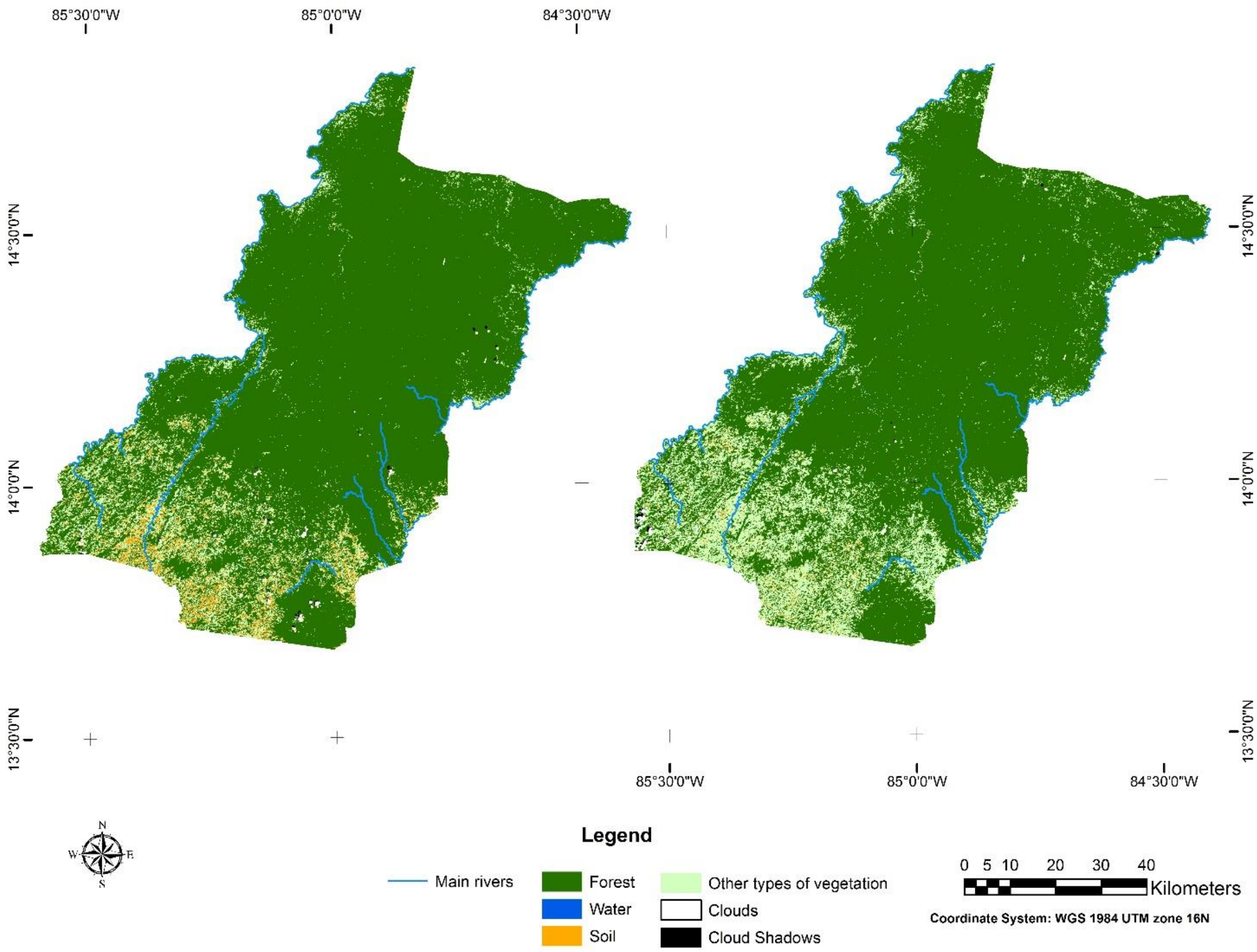

Figure 3. Land cover of the nucleus zone of the Bosawas Biosphere Reserve for 2015

4.3 Deforestation patches

After obtaining 2011 and 2015 land cover maps, this study further identifies the areas where the forest cover had disappeared. In general, deforestation patches were present across the entire study area. However, it is evident that most of the affected zones are located in the south part of the nucleus (see Figure 4). A close inspection of the numerous patches reveals at least three different pattern: linear, irregular and regular. Each of these patches can be linked to a specific real world action, as proposed by Mertens and Lambin (1997). In order to do so, the association of deforestation patterns with agents of change needs a deep analysis of the occupation history, economic, social, and environmental constraints, which is out of the reach of this study.

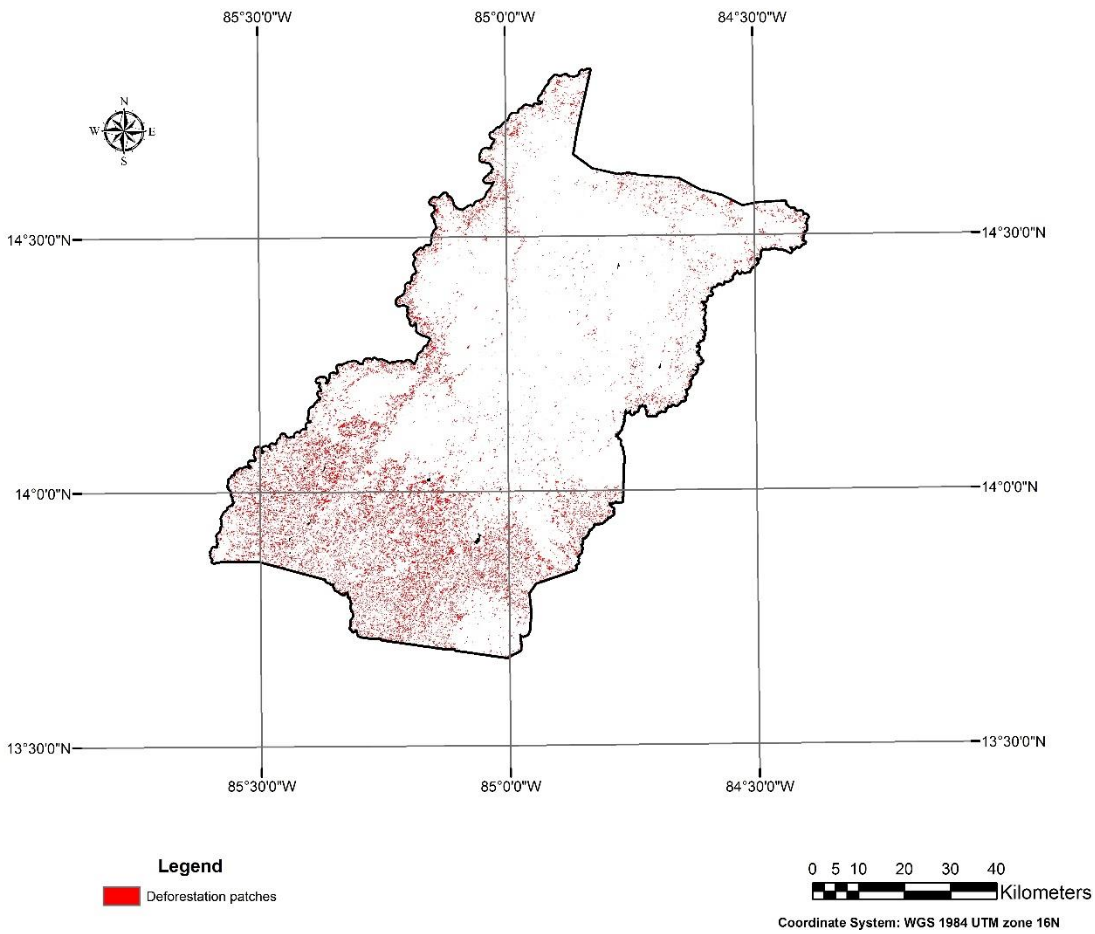

Figure 4. Deforestation patches within the core zone of the Bosawas Biosphere Reserve in 2011-2015

4.4 Analysis of deforestation patch metrics

The metrics obtained from FRAGSTAT for both types of deforestation patches, clear-cut and vegetated deforestation, are shown in Table 3. The total amount of clear cut patches was utilized (5229 patches), and a sample of vegetated deforested patches of the same size was randomly selected.

Table 3. Mean values and standard deviation of the analyzed LEM for deforestation patches

Type	Area (m^2)	Perimeter (m)	PARA	Shape	Frac	Gyrate	Contiguity	Circle
Clear-cut patches	0.60 (0.77)	345.50 (250.70)	839.36 (319.52)	1.13 (0.21)	1.04 (0.03)	29.71 (18.05)	0.32 (0.22)	0.44 (0.24)
Vegetated deforestation patches	1.48 (3.13)	640.10 (909.64)	774.65 (342.92)	1.31 (0.44)	1.06 (0.05)	45.45 (42.88)	0.37 (0.24)	0.48 (0.26)
P-value (T-test)	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

The analysis indicates that the extension of the average vegetated deforestation patch doubles that of a clear-cut patch. Consequently, the mean perimeter of clear cut patches is significantly smaller. Furthermore, these two parameter are the basis for the rest of patch metrics. As a result, the lower area and perimeter of clear-cut patches means lower shape, frac, gyrate, contiguity and circle values.

In general, vegetated deforestation patches have a more complex and convoluted shape (irregular geometry) with a higher extent, thus reaching further into the landscape. In addition, these patches are elongated and less compact but not very narrow. On the other hand, clear cut patches are more fragmented and sparse from one another (lower contiguity value). In terms of shape, these patches are still irregular, but more compact than their vegetated counterparts.

CONCLUSIONS

Examination of the 2011 land cover reveals that around 6206.77 Km^2 corresponded to broadleaf forest. This represents 86.5% of the total area analyzed. By 2015 the forest cover diminished to 5825.14 Km^2, with a net forest loss equivalent to 5% of the study area. When comparing the two classification methods, the OBC approach yielded a better accuracy result for the image of 2015, with an increase of the Kappa coefficient from 0.84 to 0.93. Deforestation patches were detected across the entire study area. Nonetheless, there is a higher concentration of patches is the south part of the study area. Most of the loss forest area was either reconverted to bare soil or other types of vegetation. The deforestation patch metrics analysis reveals that the general shape of a patch is associated with the type of land cover change. Clear-cut patches tend to be smaller and have a compact shape, whereas the vegetated deforestation patches have a more complex and convoluted shape. In order to associate the different deforestation patterns to active actors, a deeper analysis of the occupation history, economic, social, and environmental context has to be conducted in the future.

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