IMAGE CLASSIFICATION USING LANDSAT TM IMAGES TO MAPPING WETLANDS VEGETATION (*BANHADOS*) OF THE CATARINENSE PLATEAU, SOUTHERN BRAZIL.

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ABSTRACT:

Wetlands embody a diversified scope of ecosystems. This environment presents a high richness of botanical species, acting as an interface between earthly and aquatic systems providing a rich biodiversity, including endangered endemic species. Catarinense Plateau, located in Southern Brazil, presents these typical wetlands, occurring in altitudes between 800 to 1600m, yet scarcely researched about its occurrence and spatial borders. They occur in small and medium sized extensions, are frequent and occur intermingled to altitude meadows. This study aims to map and delimitate the occurrence of wetlands, and was realized in the Catarinense Plateau, localized in Santa Catarina State (between 27°30`S, 51°00`W and 28°30` S, 49°45`W). Two methods were tested in this classification: object-based and pixel-based classification. A pixel-based image analysis supervised classification was performed using Maximum Likelihood algorithm, separating two classes of features, wetlands and non-wetlands. All Landsat Thematic Mapper (TM) image process used ENVI 4.7 and ENVI EX software. The Catarinense Plateau wetlands occur in random distribution, with small and medium sized extensions, usually between 0.5 - 5 ha. The reference intersection values are bigger in pixel-based classification, however the object-oriented classification shows better the shape correlation to reference base polygons. Wetland delimitation maps are important factors to improve the conservation and good management of the ecosystem. More studies are needed so that the delimitation and extent of these wetlands can be accurately mapped.

1. INTRODUCTION

Wetlands embody a variety of ecosystems, such as swamp, mire, marsh, morass, slough, permanently or temporarily inundated, with static or flowing water, fresh, brackish or salt (Ramsar, 1971). This environment presents a high richness of botanical species, acting as an interface between earthly and aquatic systems that provides a rich biodiversity (Pollock et al., 1998), including endangered endemic species (Barbier et al., 1994).

Catarinense Plateau presents these typical wetlands, occurring in altitudes between 800 to 1600m, and they are yet scarcely researched about their occurrence and spatial borders, as well as in their diversity and ecological importance. The wetlands in this region are called '*banhados'*, a word that comes from Spanish (Burger, 2000). They occur in not very large extensions, but repeatedly and intermingled with altitude meadows. Characterized as swampy (Almeida et al., 2007), occurring in flowing water (open) and static water (isolated) systems.

The lacking of notice about wetland environment at Brazilian level, plus its botanical and ecological knowing incipience, emphasizes its problematic preservation situation. By Environmental Laws point of view you can observe that Brazilian legislation doesn't recognize this specific ecosystem as a protected one. And starting from the point that being legally established is a primordial factor to preserve biological communities (although this single fact by itself doesn´t ensures the preservation of the habitats) leads us to think that wetlands of Catarinense Plateau may be considered totally subjected to changes of its natural condition, since there are no legal mechanisms to protect it.

In this context, mapping the vegetation of wetlands zones appears as an important tool to a good management of earth resources and to preserve flora and fauna of these wet areas (Adam et al., 2010). According to Ramsar Convention – the only global environment study agreementabout conservation of this particular standard ecosystem, the wetlands – the delimitation of these areas and its map registration later, are preliminary factors to their conservation (Ramsar, 1971).

Remote sensing by satellite images presents many advantages in monitoring wetlands and it may be used in all kinds of these zones (Ozesmi and Bauer, 2002). Since the use of Remote sensing techniques enlarge the mapping alternatives, through a time waste reduction to perform observations of density and frequency of samples. In addition the segmentation/object-oriented classification showed to be an ideal technique to classify isolated wetlands (Frohn et al. 2009). Nevertheless, it's important to establish a specific classification routine in order to extract usefull ecological information (Tuxen et al., 201 approach1). Also accuracy is needed, since wetlands are not easily detectable due to herbaceous wetland vegetation

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exhibiting high spectral and spatial variability (Adam et al. 2010).

In Frohn et al. (2009) researches with object-oriented classification to delimitate isolated wet areas in Florida, with similar distribution and dimension as those of Catarinense plateau, Landsat ETM+ images were used, and obtained 88% accuracy, what indicates the possibility that, in Catarinense Plateau conditions, this methodology could be experimented to recognize the occurring wet zones.

Present study has the aim of testing object-oriented and traditional classification routines, using Landsat Mapper (TM) images to map wetlands. The use of a classification methodology on highland mapping wet zones of Catarinense Plateau will allow the elaboration of an official limit of these areas, something that is primordial to its legal protection and the conservation of this ecosystem, beyond its usefulness in outlining researches focused on this environment. Also this isthe first study to map these wetlands, and precursor in Brazil.

2. METHODOLOGY

2.1 Study Area

Researched area consists of 16.180 km^2 in Santa Catarina State Plateau, spreaded among 18 cities (between 27º30' S, 51º W and 28º30' S, 49º45' W) in Southern Brazil (Figure 1). This area was selected due to its high wetlands density and to the absence of ecosystem mapping, so far. In order to establish a specific classification routine, tests were applied at a clip area of 81 km^2 (28º07' S, 50º30' W and 28º10' S, 50º22' W) inside the Catarinense Plateau.

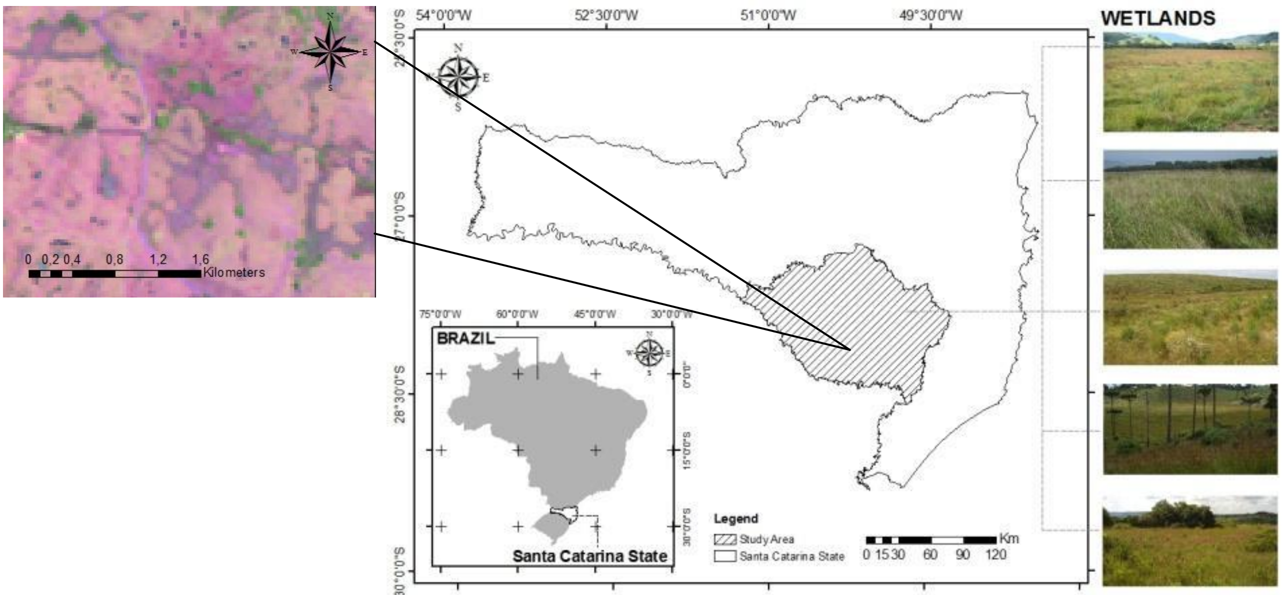

Figure 1. Catarinense Plateau's localization (hatched areas) in Santa Catarina State, at Southern Brazil (center), wetlands photos of the region (right) and Landsat Thematic Mapper (TM) image scene clipped to the study area (left).

2.2 Data acquisisition and pre-processing

Landsat TM image scene 221_079 from Jul 20 2009 acquired by National Institute for Space Research (INPE; available from http://www.inpe.br) was used in test area, besides GeoCover Sirgas 2000 mosaic images, available by National Aeronautics and Space Administration, (NASA; available from http://zulu.ssc.nasa.gov/mrsid/mrsid.pl). The scene used for the preliminary tests in this study was the wettest of 2009.

The Landsat images were commonly used in mapping wetland vegetation (Adam et al. 2010) and showed a good accuracy (Baker et al. 2006). In addition the Landsat data provide adequate temporal, spatial, and spectral resolutions for detecting wetlands that are ≥ 0.2 ha (Frohn et al. 2009, Fronh et al. 2012).

This study used a multispectral composition to 5, 4 and 3 bands (Table 1), considered the best band composition to wet zones detection (Ozesmi and Bauer 2002), it has already been used in several researches on wet zones, including those in Brazil (Giovannini 2004, Rocha et al. 2011, Cardoso et al. 2011). The 5 band is considered by many authors, as the most important one in delimitation of wet lands, for its ability to discriminate vegetation and humidity levels (Ozesmi and Bauer 2002, Frohn et al. 2009).

Band	Spectral (μm)	Spectral	Use
3	0.63 – 0.69	Visible	Water absorption
4	0.76 – 0.90	Near-infrared	Vegetation
5	1.55 – 1.75	Mid-infrared	Soil humidity

Table 1. Landsat Thematic Mapper (TM) image bands used in Minimum Noise Fraction (MNF) transformation and hyperspectral data composite.

The image scenes were radiometrically corrected using FLAASH method after the image radiance calibration in ENVI software (Exelis Visual Information Solutions).

The images were registered using 9 control points, originated from Geocover Sirgas 2000 mosaic, considering a risk mistake of Root Mean Square (RMS) equal or lower to 0.8 picture element. Polynomial Mathematical models have been chosen.

2.3 Data transformation

Two transformations were applied to Landsat TM data to improve the potential classification of wetlands 1) a minimum noise fraction (MNF) transformation, 2) a texture transformation based on co-occurrence in band 5.

After register, date rotation was implemented aiming to enhance the wetlands areas (Figure 2). The methodology utilized was the one proposed by Frohn et al. (2009), the MNF that establishes dimension of the dates and enables the remove of noises, which are information that cause class mixture. The MNF rotation was applied again in the images, however, using noise dates generated in the first rotation. According to Frohn et al. (2009) isolated wet zones are clearly visible in minimum fraction noise transformation.

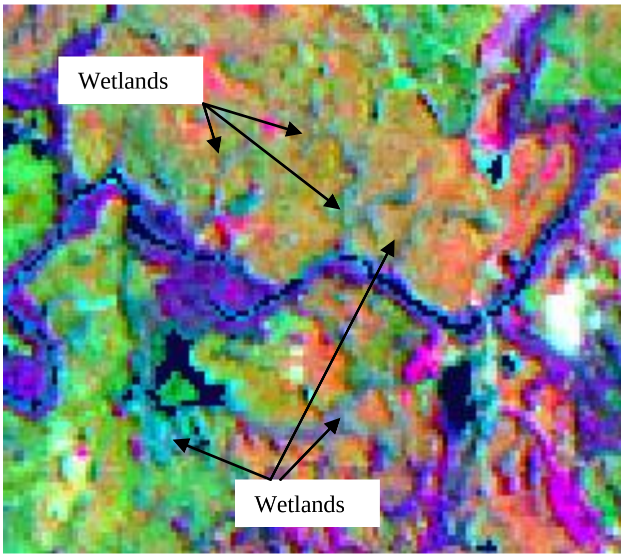

Figure 2. Minimum Noise Fractium (MNF) transformation showing wetlands (in blue).

Was used a hyperspectral image compost by 1) first band of MNF transformation, 2) a texture co-occurrence of 5 band, 3) a ratio 4 band to brighthness, 4) 5, 4 e 3 bands.

2.4 Image classification

Two methods were tested in this classification: traditional classificatory (pixel-based) and object-based image classification. In both, pixel-based and object-based classification, two classes of features were created, wetlands and no wetlands.

In pixel-based method was tested supervised classification and unsupervised classification disposal in ENVI EX software. In supervised method were selected regions of interest to wetlands and no wetlands. The test area was classified using the Maximum Likelihood, Minimun Distance, Mahalanobis Distance, Spectral Angle Mapper algorithms. In unsupervised method used K means algorithm. The classification data it was used 5, 4 and 3 bands and MNF image transformation.

The object-oriented classification applies hyperspectral composite to select wetlands with rule-based technique. Feature extraction uses an object-based approach to classify imagery based on spatial, spectral, and texture characteristics. In order to obtain feature extraction it's necessarily to use segmentation process of partitioning an image into segments by grouping neighboring pixels with similar feature values (brightness, texture, color, etc.) to find objects.

In object-oriented classification data was segmented at scale of 10.00 and merged at 50.00. The parameters were defined by trial and error approach in order to acquire image objects similar to wetlands. Rule-based classification was made for trial and error, and was based in the rules used for Frohn et al. (2009). Rule-based aplplied, 1) Spatial: area, 2) Texture: texture mean, 3) Spectral: band 4 mean, band 1 of MNF mean, co-occurrence in band 5 mean.

2.5 Classification accuracy

Wetlands were identified based on the intersection of reference polygons in two areas inside the tested area. In order to validate the proposed method, its accuracy was analyzed overlaying the vectors obtained in test areas obtained from Google Earth images, in which were possible to identify wetlands. This comparison was necessary since the researched area no have cartography maps (actual and ancillary). Also the study doesn't have images from which to compile a comparison map.

All image processing used ENVI 4.7 e ENVI EX 1.0 software. The statistical analyzes and graphical productions were use R software, free source (R Development Core Team 2005). The accuracy analysis used ArcGIS 9.3 software.

3. RESULTS AND DISCUSSIONS

In pixel-based classification the parameters were defined by trial and error approach in order to acquire image objects similar to wetlands. The Maximum Likelihood Classification (MLC) showed the best algorithm in pixel-based to classifying wetlands. MLC there were a total of 357 wetland polygons bigger than 0.5 ha identified in the test area. The wetlands occur in small and medium sized extensions, between 5077m^2 to 714577m^2 (Figure 3, left) with an average of 44420m^2.

Using object-oriented classification there were a total of 492 wetland polygons bigger than 0.5 ha in the test area. The wetlands occur in small and medium sized extensions, between 5077m^2 to 541509m^2 (Figure, 3 right) and mean 23247m^2.

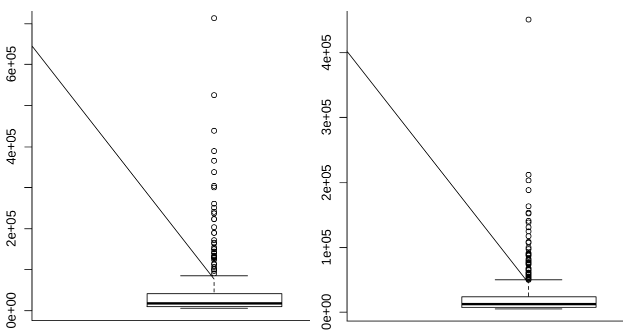

Figure 3. Boxplot graphic showed the size distribution of wetlands in test area using Maximum Likelihood Classification (MLC) (left) and object-oriented classification (right).

In test area of oriented-object classification the wetlands showed small and medium sized extensions, between 0.5 to 5 ha. Its occurrence is frequent, random and doesn't have a standard distribution (Figure 3).

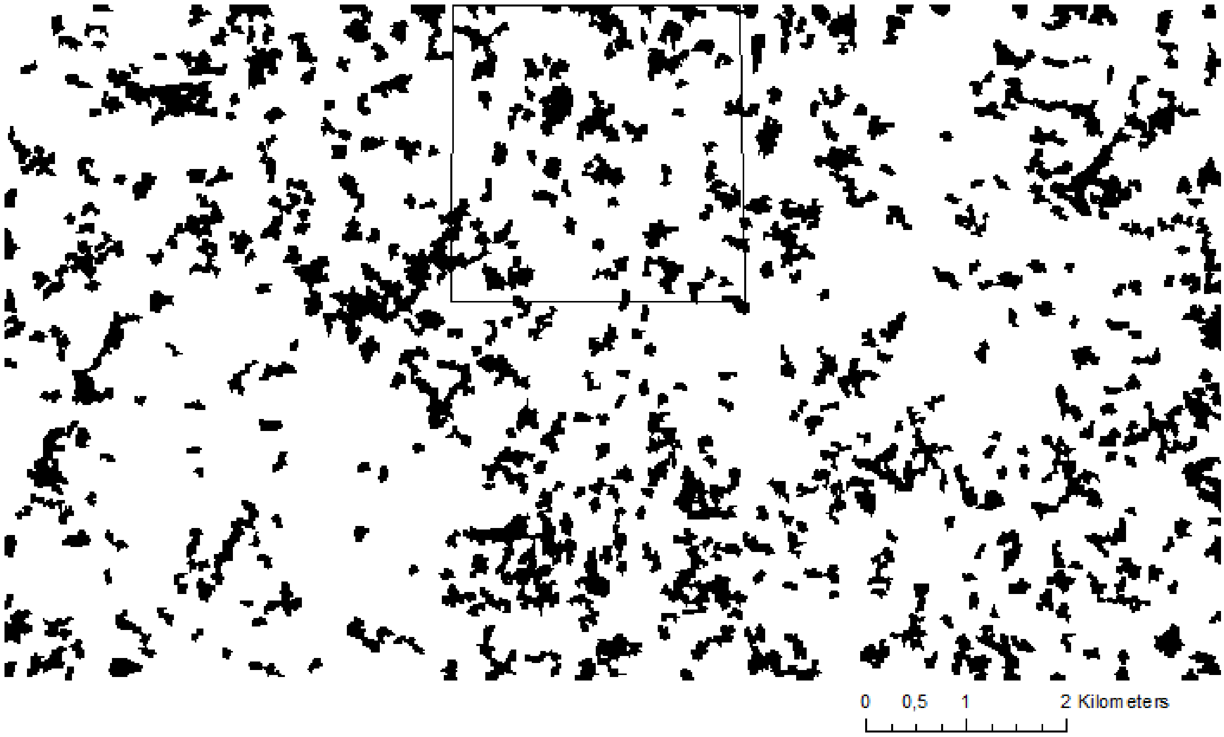

Figure 3. The final object-oriented classification of wetlands. The inset box is presented at a finer scale in Fig. 4 and 5.

The intersection of reference polygons inside the test area was used to analyze the accuracy. The intersect values were bigger in pixel-based classification (31.94 and 60.97 ha) than in object-oriented classification (19.26 and 34.85), but mean and sum in oriented-object classification are nearest to reference based in both test areas (Table 2).

	Polygon	Sum (ha)	Mean (ha)	Standard Deviation
Area 1				
Base	56	79.30	1.42	3.13
Pixel	44	163.22	3.71	5.12
Object	47	124.09	2.64	3.69
Intersect Pixel/base	44	31.94	0.73	0.68
Intersect object/base	38	19.26	0.51	0.57
Area 2				
Base	50	96.14	1.92	2.11
Pixel	41	179.06	4.37	7.26
Object	61	177.05	2.90	5.89
Intersect Pixel/base	42	60.97	1.45	1.52
Intersect object/base	50	34.85	0.69	0.66

Table 2. Statistic data of pixel-based classification, object-oriented classification and reference polygons from Google Earth image.

The visual performed of pixel-based and oriented-based classification overlapping reference data can be visualized in Figures 4 and 5.

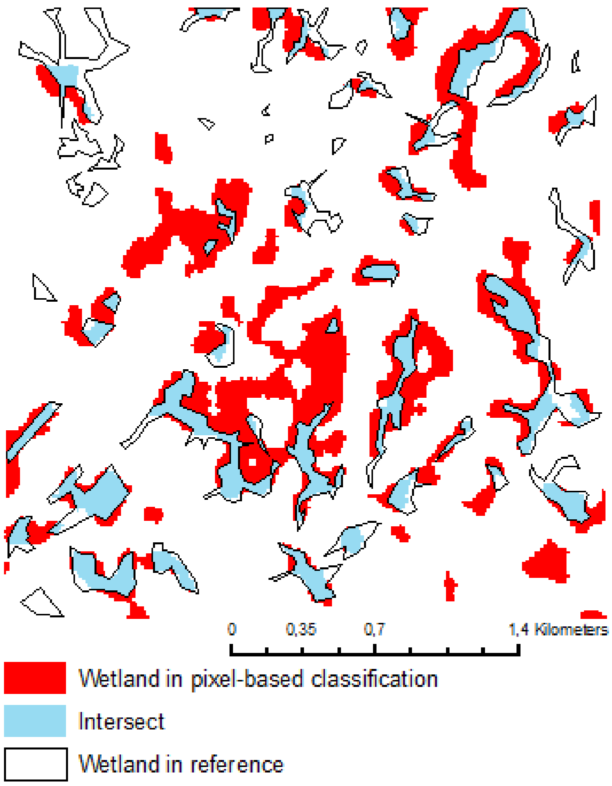

Figure 4. Overlapping Maximum Likelihood Classification (MLC) polygons (in red), reference base (black line) and intersect (in blue).

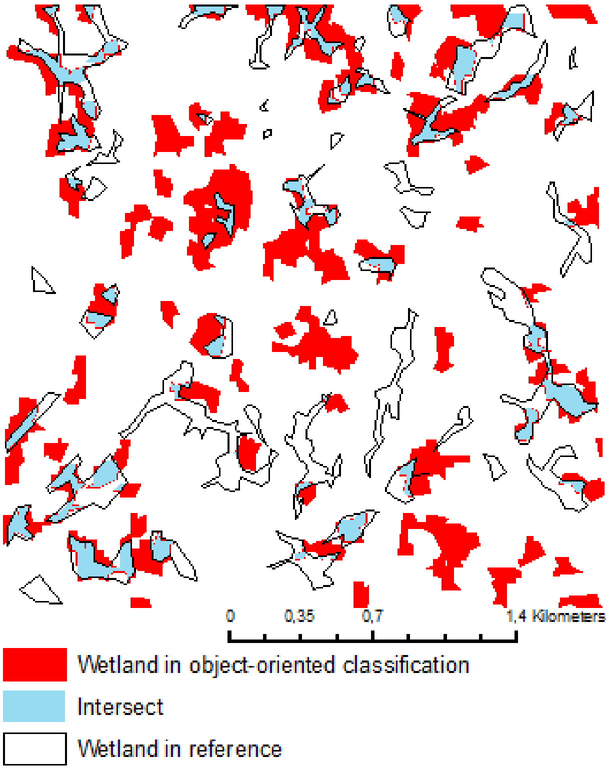

Figure 5. Overlapping object-oriented classification polygons (in red), reference base (black line) and intersect (in blue).

Although the pixel-based classification has intersected more areas than object-oriented classification, this classification showed better shape correlation to reference base polygons (Figure 6).

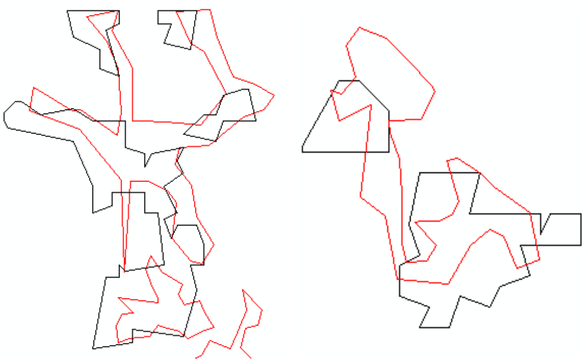
Figure 6. Comparison of wetlands object-oriented classification boundaries (black line) overlapped in wetland bounders of reference base (red line).

It should be emphasized that the date of reference data is November 2005 and that of the Landsat TM image is July 2009. A great part of the difference between classification results is due to the dynamic of wetlands ecosystem, since its wet area, size and shape, can change from year to year (Frohn et al. 2009).

So far wet zones classification presents a series of limitations. Wetlands can also be confused with agricultural and forest classes because of overlapping spectral signatures (Ozesmi and Bauer 2002).

This research is a preliminary study and need to be improved, however the methodology showed itself to be appropriated to mapping wetlands in Catarinense Plateau.

4. CONCLUSIONS

The wetlands in Catarinense Plateau occur in a random distribution, they have small and medium sized extension, usually between 0.5 of 5 ha.

The object-oriented classification showed a better conservation of shape and distribution of the wetlands.

MNF image transformation was a good technique to identify wetlands.

More studies are needed so that the delimitation and extent of these wetlands can be accurately mapped. And some other classificatory methods would be tested as the map methodology improves. The elaboration of a delimitation of these areas is primordial to the management and conservation of this ecosystem, besides to making public its existence and importance.

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