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A Quantified Analysis of Urban Sprawl Based on High-Resolution Satellite Remote Sensing

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Abstract
Under the circumstance of global sustainability, the expansion of urban has been paid serious attention by governments. To obtain the harmonious symbiosis with nature, decision-makers need a reasonable method to quantify and monitor the urban expansion. This paper analyzes a particular area through spatiotemporal identification and quantification by using high-resolution satellite images. The change trend and ratio of artificial construction areas in the research area from 2016 to 2023 are analyzed. Optical flow is chosen for visualization and analyzing the characteristics of urban expansion in the research area, directly expressing the quantity and direction of construction in the process of urban expansion, which cannot be reflected in the traditional image quantitative analysis. The results show that the urban is expanding to the coastline and causing irreversible damage to local natural environment. The proportion of vegetation coverage should be strictly controlled.

Keywords
Ecological Balance, GF-2, High-Resolution Satellite Images, Urban Sprawl

1. Introduction

Appropriate urbanization can improve the living environment through land leveling, infrastructure development, urban greening, and other strategies [1]. However, rapid urban sprawl, especially in developing countries, has changed the function of regional ecology and habitat, causing potential threats to the environmental balance and sustainability [2]. Immoderate urban sprawl leads to temperature rising as human activities decrease green spaces and water areas, which directly impacts our environment [3]. Monitoring urban expansion and suggesting a probable scenario of future development, is essential for achieving sustainability.

Urban sprawl refers to the uncontrolled, excessive, and inefficient expansion of urban areas, which leads to the decline of land use and population density, and the increase of traffic, environmental, and social problems [4]. Urban expansion is a complex and dynamic phenomenon that requires effective methods and data sources to monitor and analyze. Previous studies have used various approaches to measure and evaluate it, such as remote sensing (RS) and geographic information systems (GIS), statistics

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and econometrics, and simulation and prediction. For research urban sprawl, RS and GIS are always used to analyze the dynamic changes and characteristics by satellite images and spatial data [5]; statistics and econometrics methods are used to evaluate the influencing factors and effects; and simulation and prediction, which use mathematical, computer, and intelligent models to simulate and predict the process and outcome of urban sprawl [6].

However, the quality and availability of satellite images, which may differ in spatial and temporal resolution, coverage, and accuracy, affecting the performance of RS/GIS methods. Different image processing techniques and indicators may lead to inconsistent or incomparable results, and the selection of a specific sensor for any RS application depends on various factors, such as cost, spatial, spectral, and temporal resolutions of the images [7]. Statistics and econometrics methods depend on the availability and reliability of various data sources, such as census, land use, and socio-economic data. The existing analysis methods cannot provide intuitive and effective suggestions for the future expansion direction of the urban area. In addition, simulation and prediction methods require the selection and calibration of appropriate models, parameters, and scenarios, which may involve subjective judgments and uncertainties. To achieve sustainable urban development, there is still a lack of efficient evaluation and analysis method of urban sprawl, especially in developing cities [8].

This paper quantifies the spatiotemporal patterns and impacts of urban expansion in Xuejiadao from 2016 to 2023 using high-resolution satellite images (HRSIs) and optical flow. HRSIs were processed and analyzed with ENVI and GIS to determine building expansion trends. Optical flow, which is a deep learning network used to address optical flow estimation problems, is used to determine the main area and direction of expansion. The value of HRSIs for urban sprawl study is shown in this research, as they can provide more realistic and reliable data and improve research accuracy and efficiency. This research can intuitively and effectively analyze the current problems of urban development and the potential threats and impacts on the surrounding natural environment, providing more accurate guidance and suggestions for timely and effective adjustment of urban development direction and policies.

This paper is organized as follows: Section 2 presents the HRSIs processing workflow. In Section 3, the urban expansion characteristics of research area over three different years are illustrated and visualized. Section 4 analyzes and discusses the reasons for the expansion trend of the artificial construction area and concludes this paper.

2. Methodology

This study aimed to analyze and quantify the urban expansion in research area by using HRSIs and optical flow estimation. Gaofen-2 (GF-2) satellite imagery was employed to conduct a quantitative analysis of the construction area expansion and assess its impact on the surrounding ecological environment. Furthermore, Normalized Difference Vegetation Index (NDVI) was chosen as the calculation formula for identifying buildings to determine the proportion of regional construction volume. The methodology consisted of four main steps: data acquisition and processing, index calculation and threshold determination, optical flow estimation and visualization, and spatiotemporal analysis of urban expansion. The major research process is shown in Fig. 1.

2.1 Research Area

The research area is Xuejiadao in Qingdao City, China. It covers an area of 837.83 km² and has a

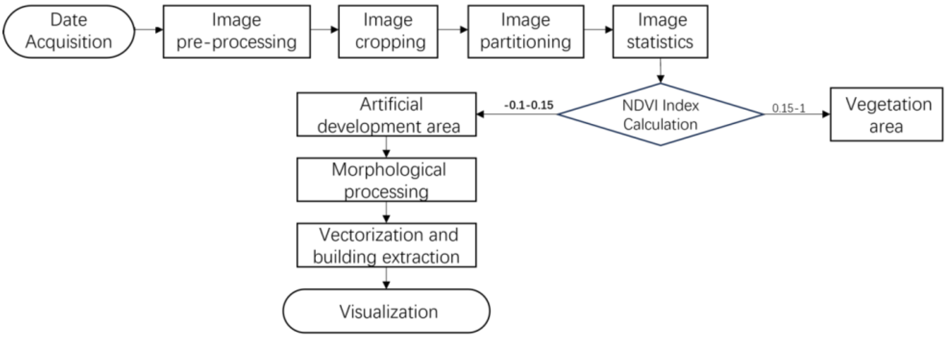


Fig. 1. The main structure of the research process.

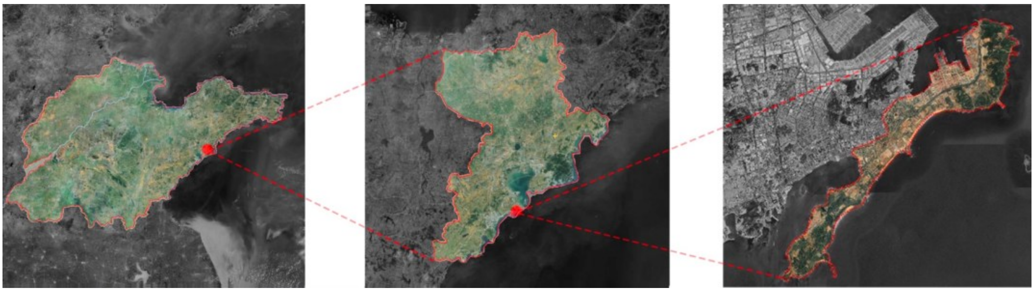


Fig. 2. The location of research area.

population of about 71,000. It also has a temperate climate that provides a pleasant environment for its residents and visitors. Qingdao Economic and Technology Development Zone, which is a key industrial and commercial hub in the area, is located here. In recent years, Xuejiadao's rapid economic development has also faced a series of challenges brought by urban expansion, such as traffic congestion, environmental pollution, housing shortage, and public service deficiency, which is illustrated in Fig. 2.

This region is an ideal case for urban expansion research because it combines fast urbanization, distinctive natural and social features, and the persistent tension between urban development and environmental conservation. These factors illustrate both the general pattern and the specific characteristics of urban expansion, offering new perspectives for understanding this phenomenon.

2.2 Data Acquisition and Processing

Change detection is an essential subject in the field of remote sensing. HRSIs are acquired from China's GF-2 satellite that is the most advanced civil satellite in China. The GF-2 has a high-resolution panchromatic camera with 1-m resolution and a multispectral camera with 4-m resolution.

The quality of remote sensing images is largely influenced by the meteorological conditions [9]. Meteorological conditions, such as cloud cover, aerosol concentration, humidity, and solar zenith angle, affect the quality of remote sensing images. These factors can scatter, absorb, and attenuate the electromagnetic radiation that captures the images of the earth's surface, resulting in reduced contrast, blurred edges, distorted colors, and increased noise. To obtain high-quality and consistent images with minimal cloud, shadow, and atmospheric interference, the time periods with cloud cover less than 3% are selected. The noise is filtered out and the contrast is enhanced to better identify and compare the land use and urban development features and patterns across different time periods.

Considering that the construction of urban engineering projects and the growth of vegetation need a certain period, selecting a time interval of every 3–4 years for observation and analysis was deemed suitable, given the increased clarity of changes over this period. Winter is not selected as the cloud cover, image availability, and vegetation cover are low, and the images are less suitable for urban or agricultural land change research. Therefore, the time periods with low cloud cover from April to September are generally chosen. Thus, to avoid these negative effects, this paper selected satellite images of the research area from 2016, 2019, and 2023 on sunny days with less than 3% cloud cover for quantitative analysis. The indexes of the selected HRSIs are shown in Table 1.

Table 1. The information of selected GF-2 images

Product number	Time	Path	Row	Cloud cover
1806532	2016.09.05	1006	149	0%
4056030	2019.06.13	1006	149	1%
7230202	2023.04.17	1006	149	1%

To accurately analyze GF-2 remote sensing data, the data is preprocessed and converted into usable digital format. The processing contains calibration correction, orthorectification, and fusion to the panchromatic, and multispectral images [10]. Radiometric correction can eliminate differences between different bands, which uses the following equation to convert DN values from raw data to radiometric values:

$$L_e = Gain \times DN + Offset, \tag{1}$$

where L_e is the radiant brightness and $Gain$ and $Offset$ are calibration coefficients obtained from the China Resources Satellite Data Application Centre.

The orthographic corrected data has a consistent geographic coordinate system, which can be applied in combination with GIS. The raster layer of the image fusion result and the vector layer of the administrative boundary were imported into ArcGIS. The polygon feature of the research area was used to crop the raster layer using the Clip tool, resulting in a raster layer that only covered the Xuejiadao area. The vector layer of the coastline was imported and the coastline feature that intersected with the polygon feature was selected using the Select by Location tool. Buffer zones of 200 m, 400 m, etc., were created from the coastline feature using the Buffer tool and used to crop the raster layer again using the Clip tool. This step produced multiple raster layers that showed the image fusion result at different distances from the coastline. The statistics of each raster layer, such as the mean, standard deviation, minimum, maximum, and count of pixel values, were calculated using the Raster Statistics tool.

2.3 NDVI Index Calculation and Threshold Determination

NDVI is a common indicator of vegetation greenness and health at both regional and global scales and is frequently used in vegetation research. A key research area is the classification and identification of land cover types using NDVI data. NDVI is calculated as follows:

$$NDVI = \frac{\{NRI - R\}}{\{NIR + R\}}, \tag{2}$$

where *NRI* is near infrared band, and *R* is infrared band.

Because of the different proportions of near infrared and red light reflected by building materials, such as concrete and metal, compared to vegetation. In remote sensing images, buildings often show up as areas with lower NDVI values, normally from -1 to 0.15. However, it is important to note that NDVI does not directly reveal the extent of buildings. Therefore, even though NDVI may not directly delineate the extent of buildings, it can provide useful hints about potential building locations through the analysis of NDVI value distributions. It signifies the lack of vegetation and can indicate urban areas, roads, buildings, exposed soil, and rocks. For instance, any elements with an NDVI value above 0.15 are classified as vegetation and trees. In this research, the NDVI values from -0.1 to 0.15 were used to represent the artificial development area within the research area.

The resulting binary images were then processed by morphological operations to remove noise and isolated points and improve the connectivity and integrity of the buildings. Finally, the optimized binary images were vectorized, and the boundaries and attributes of the buildings were extracted, obtaining the vector layers of the buildings

2.4 Visualization

FlowNet is a deep learning network used to address optical flow estimation problems. Optical flow estimation is an important task in computer vision, aiming to estimate the motion vector of each pixel in an image, which is the displacement of that pixel between two consecutive images. In the following indicator image, the colors represent the direction of movement, and the color intensity indicates the predicted magnitude of movement. In this research, optical flow maps are used to visualize the quantity and direction of urban expansion in the research area.

The resulting image is processed based on the optical flow algorithm of PyTorch framework. The optical flow algorithm processing flow is as follows: the images of two different time points are input into the Flownet2 model. The model extracts the feature representation of the images through convolutional neural network (CNN), matches the features of the two images, finds the corresponding feature points, and uses the corresponding pair of feature points to calculate the pixel-level displacement vector, that is, optical flow. Optical flow estimation is achieved by predicting the displacement vector of each pixel. The corresponding color is used to identify the result of the optical flow estimation.

3. Experimental Result

The artificial development areas are identified in the years of 2016, 2019, and 2023, which is shown in Fig. 3. The development area in 2016 was 5.100 km², which increased to 5.365 km² in 2019 and further expanded to 6.051 km² by 2023, as shown in Fig. 4. The expansion of human activities has led to a reduction in the overall coverage of natural green vegetation, posing a growing threat to their survival and the overall ecosystem.

Using GIS software, vector files of the coastline and building vectors within the study area, establish buffer zones 100 m, 200 m, and 300 m from the coastline for the years 2016, 2019, and 2023, respectively. This paper selects the building area within the buffer zones by location, identifies and calculate the building area within the buffer zones for the years 2016, 2019, and 2023, and extracts the buildings within different buffer zones across the three years. The building area at different distances from the coastline in different years can determine the main expansion areas and direction of buildings.

The overall building area shows a trend of growth in Fig. 5, with a rapid increase from 2016 to 2019 and a slower increase from 2019 to 2023. The increments in building area differ at different distances from the coastline. The primary expansion of buildings from 2016 to 2019 was in the range of 100 m to 200 m from the coastline, while from 2019 to 2023, the main expansion area was within 100 m of the coastline.

The visualization results from the optical flow diagram (Fig 6) show that the optical flow diagram illustrates that from 2016 to 2019, the construction zone close to the shoreline (100 m to 200 m) experienced significant growth. From 2019 to 2023, the development persisted, albeit at a reduced pace, primarily within 100 m of the shore. Overall, the built-up area modestly extended towards the coast.

In this study, HRSIs from the years 2016, 2019, and 2023 were selected. The optical flow between images of adjacent years was estimated, resulting in optical flow fields for the periods 2016–2019 and 2016–2023 (Fig. 7). The saturation levels within these optical flow fields serve as pivotal indicators of urban expansion intensity. Elevated saturation levels denote a pronounced migration of structures towards the coastline, predominantly in the eastern and central sectors of Xuejiadao. The analysis of these fields indicates that urban sprawl is chiefly concentrated in coastal proximities, with the eastern and central regions experiencing more substantial shifts. In stark contrast, the western and northern territories maintain a semblance of stability, evidenced by lower optical flow saturation, which suggests a lesser extent of movement. These findings are in consistent with prior analyses concerning the evolution of built-up areas.

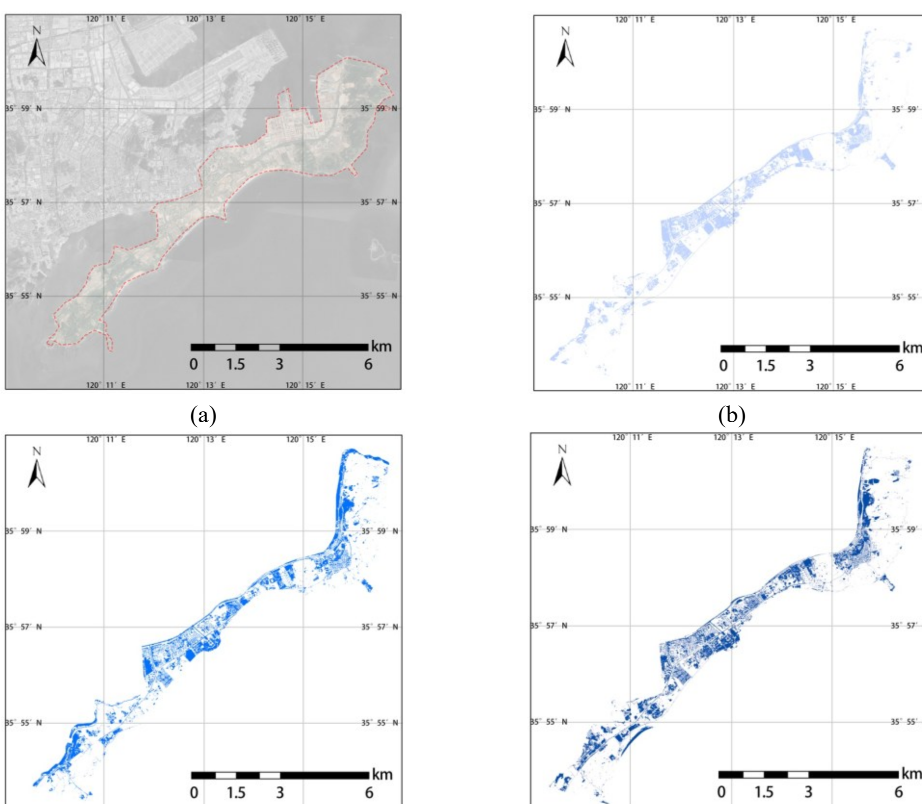


Fig. 3. Identified artificial development areas in different years: (a) high-resolution satellite image of the research area and (b, c, d) areas of construction in 2016, 2019, and 2023, respectively.

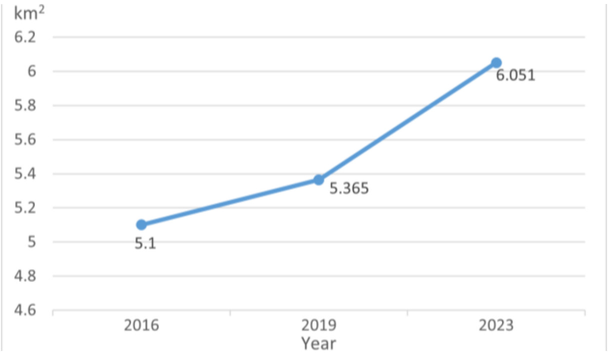


Fig. 4. Changes in the construction area.

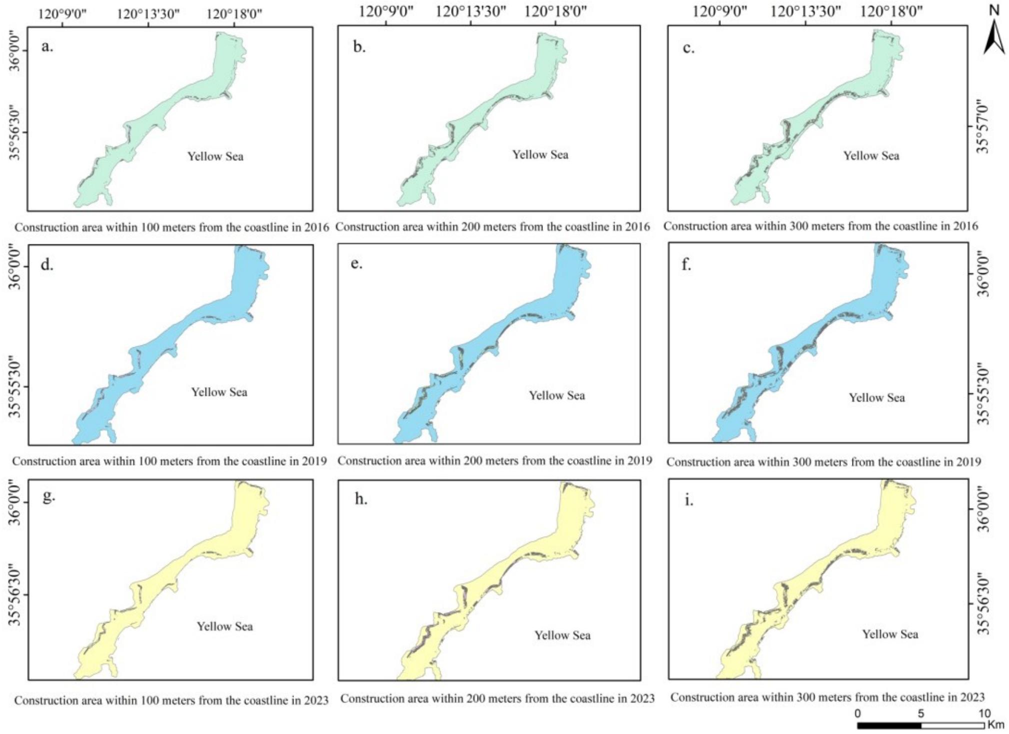


Fig. 5. Changes chart in the construction area.

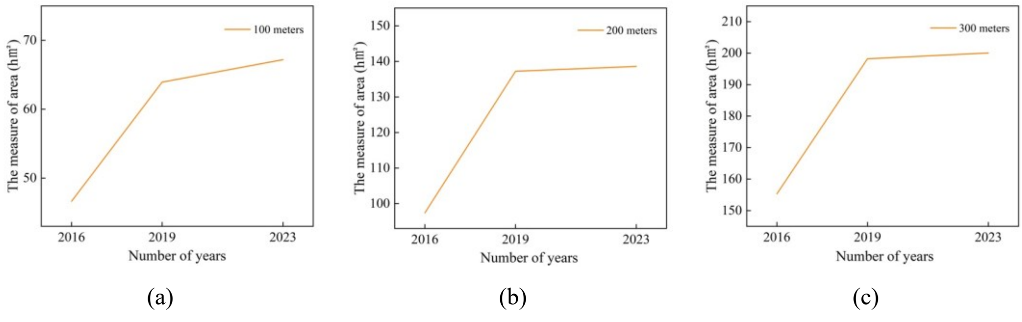
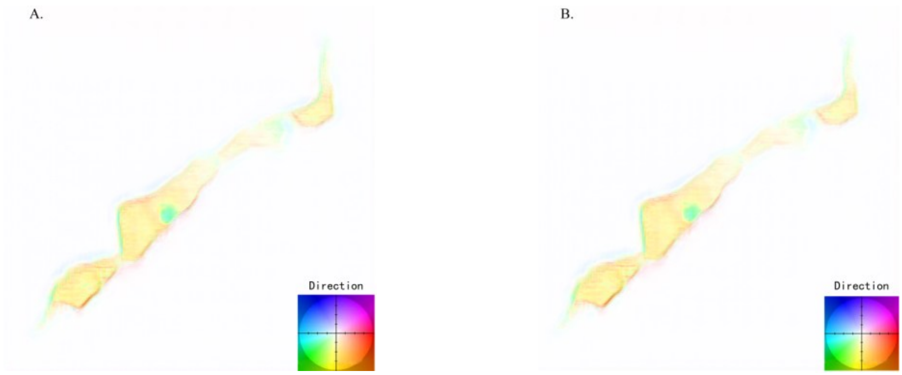


Fig. 6. Line chart of building area change: (a) 100 m, (b) 200 m, and (c) 300 m.



(a) (b)

Fig. 7. Optical flow diagram of (a) 2016–2019 and (b) 2016–2023.

4. Discussion and Conclusion

This paper analyzes the spatiotemporal patterns and impacts of urban expansion in Xuejiadao, Qingdao City, using the HRSIs from 2016 to 2023. The HRSIs can provide more realistic and reliable inputs for urban models than RS/GIS data, with better performance on the validation and calibration of model outputs. Optical flow maps can not only directly express the quantity of construction in the process of urban expansion, but also clearly indicate the direction of expansion, which cannot be reflected in the traditional image quantitative analysis. Combined with the actual urban landscape pattern, optical flow maps can accurately analyze whether the current development of the city has caused damage and threat to the main ecological environment. It is helpful for the government to adjust the direction and intensity of urban construction in time.

The results show that the urban and building areas of Xuejiadao increased substantially, especially near the coastline. The building area growth varied at different distances from the coastline, with the main expansion area shifting from 100 m to 200 m in 2016–2019 to within 100 m in 2019–2023. Meanwhile, the vegetation cover and greenness decreased, as indicated by the NDVI values. The urban expansion also led to an uneven and diverse distribution of building density across the study area, with higher density and diversity in the central and eastern parts, and lower density and diversity in the western and northern parts. In general, the urban construction in this region mainly develops along the coastline, and less woodland erosion in the central.

The paper suggests that to mitigate the severe ecological consequences of urban expansion, sustainable solutions such as green infrastructure should be prioritized. Although the urban expansion in this area has not destroyed the main vegetation cover in the central part, as a natural scenic area, the ecosystem in this area needs to be taken seriously. The reduction of vegetation in coastal areas will inevitably aggravate the impact of sea breeze erosion on the natural environment. The proportion of vegetation coverage should be strictly controlled while the coastal areas are further constructed.

Conflict of Interest

The authors declare that they have no competing interests.

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