




Land cover analysis of two university campuses: Examination over satellite images by Chat GPT

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Abstract

Land Use and Land Cover Analysis are important in detecting the changes in urban areas, rural areas, and focused lands like university campuses. The availability of high-quality satellite images from diverse time sequences makes evaluations for changes by time possible. The analysis methods include insights from remote sensing fields to Artificial intelligence (AI) tools. AI has been significantly developed in the last decades in various fields, and applications of AI on satellite imagery analysis are being influenced. This study explores the capability of Chat GPT, which is one of the leading Language Models and can generate prompts and analysis due to inputs for Land Cover and Use Analysis. Firstly, an unstructured conversation with Chat GPT was held, and then, considering this experience, a land cover change analysis was executed for two university campuses. Besides, the analysis was also re-executed in Colab with codes generated by Chat GPT to seek differences. Two university campuses, Erzurum Technical University and Adıyaman University, founded in the last two decades, were utilized as case studies. Chat GPT explained the steps and procedure of the analysis in detail generated codes in a defined framework. The analysis results have problems in classifying the land cover; however, the imperviousness change analysis shows most of the construction improvement. The experiment and findings have important implications for future research in Land Cover analysis implementing AI tools.

1. Introduction

Research and studies on land use and cover changes have important contributions to the analysis of plans in diverse areas [1]. The data originating from the satellites allows many types of explorative studies for ground and underground. The availability of this big data also offers some opportunities for the development of many aspects of urban living [2]. Among many applications of satellite imagery, Land-use-land-cover (LULC) plays an important role in urban planning resource management and presents valuable results for various research activities [3–7]. While traditional inventories and surveys are commonly used to determine LULC, satellite remote sensing offers a more efficient and cost-effective method for assessing geographical distribution and temporal changes in LULC on a regional scale. Besides, Satellite image analysis provides an effective way to learn about the trends, changes, and developments [8–10].

Accurate LULC maps are important for monitoring, planning, and managing the Earth and remote sensing studies [11–13]. Besides, the Geographic Information System (GIS) is one of the important tools for documenting, storing, evaluation and presenting sites for making accurate decisions [14–16]. Remote sensing is capturing the information of an object or land t through sensing either own or artificially emitted electromagnetic radiation [17]. The information obtained from all these fields can be used for many disciplines: mapping, architecture, cultural heritage, urban planning, infrastructure, mining, etc. Also, they can be used for climate detection, monitoring flood disasters, crisis management, and obtaining detailed terrain information [18, 19]. The industries take benefits of Satellite Image analysis, LULC, and GIS for their focused research and quantitative and qualitative studies [20, 21]. Besides, Unmanned Aerial Vehicles (UAV) are used with and without the integration of GIS and Satellite

Imagery to evaluate and analysis the elements of environment and buildings in remote sense. The calculation of buildings areas [22] and deterioration analysis of historical village house[23] by UAV method are some examples from the literature. The obtained data from UAV can be used by the implementation of point cloud and orthophote for the areas which are hard and dangerous to access [24].

Many studies are both for developing methods and exploring the possibilities of LULC. The vegetation analysis over satellite images is one of the general observation methodologies [25]. Long-term land use/cover analysis as done in Kahramanmaraş City Center by remote sensing and integration of GIS [8], analysis of changes in Mersin City with improving process [26], Land cover change bt the possible sea level rise [27] and land cover prediction [28] are also some important usage of the possibilities. With the improvement of Artificial Intelligence, LULC has started to integrate the possible usage of statistical models, machine learning and deep learning approaches [29] and also Language Models like ChatGPT. The capability of Chat GPT to generate codes, formulas, and analysis makes interdisciplinary studies like LULC possible for urban development track. This study mainly focused on seeking the possibilities of ChatGPT for land cover change analysis of university campus development. The objectives are to explore the general LULC studies, underline the importance of campus development, and explore the integration of Chat GPT in land cover change analysis over satellite images to track campus development.

1.1. Studies with Chat GPT

Artificial intelligence has affected many disciplines and sectors by releasing reachable AI tools. It offers systematic capabilities of reasoning based on inputs, learning via differences, and prediction [30]. Research in education, health, marketing, production, design, automation, and image processing can be found in the literature [31–37]. The LULC and remote sensing studies have also been affected by Chat GPT to explore the possibilities for prompt generation and analysis procedures.

A former study explores diverse AI tools' capabilities for location recognition, image captioning, and Land Use/Cover Classification by presenting strengths and weaknesses [38]. Generally, the examination successfully recognizes the objects and buildings. However weak for giving quantitative information as the number of buildings or coordinates. In another study, using Language Models for interaction with geospatial datasets was explored by training and generating information instead of traditional interaction between humans and software for geospatial data [39]. Yuan created a system for training and evaluating high quality satellite images by ChatGPT captions [6]. Wang summarizes the contemporary trends in integrating GPT with geospatial science research based on publications obtained from different academic databases [40].

1.2. University Campuses

A campus is a place in which there are diversified functioned buildings, streets, squares, courtyards, sports, and recreational zones providing services with distinctive community [41, 42]. Besides the facilities for education and research, housing, health, and cultural units are essential for self-sufficient university campuses [43, 44]. The universities are developing according to their master – plan in the long term, and the usage of land changes over time-related to the construction plan. The planning typologies, functions of the zones and buildings, and transportation framework are part of the university campus design field, guiding the critics of the design, success, and educational relations. The construction process of any campus is tracked and monitored, and the maps and land use/cover are updated for different evaluations and decision-making processes.

2. Method

2.1. Experiment Flow

The experiment started with an unstructured conversation with Chat GPT 4o¹ to analyze satellite images for land use to explore capabilities and define the research limits and framework. Examples from unstructured conversations were also presented in the results section. The overall research flow is given in Figure 1.

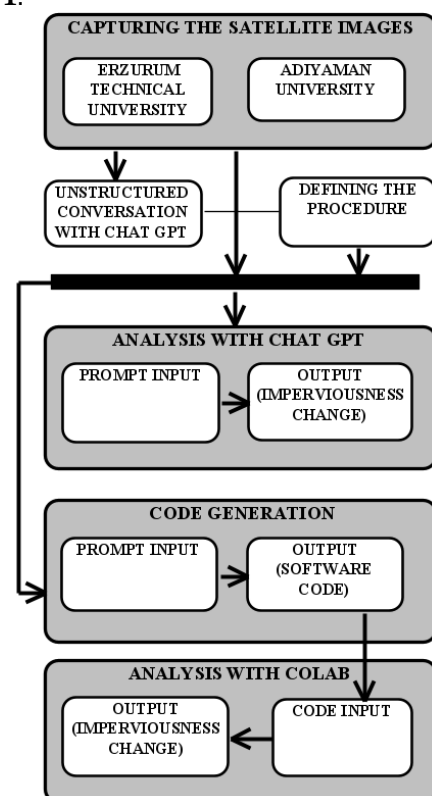


Figure 1. Research Flow

Unstructured conversation with Chat GPT contributes to the defining process since this experience was for seeking the possible research scenarios about land cover/ use analysis. It should be noted that during sessions two days, Chat GPT refused to execute analysis

¹ The used version (paid subscription) of Chat GPT at 15.06.2024.

by itself, preferring software code to be run on other platforms. The generated codes were run in Colab environment which is cloud based platform. There may be diverse platforms that may contribute to the analysis considering the data science applications or machine learning, however for evaluating the primary capabilities of the Chat GPT for code generating, the defined flow was used.

2.2. Study Area and Material

Two campuses were selected to analyze land cover changes to explore the development. One is Erzurum Technical University (ETÜ), and the other is Adiyaman University Campus.

ETÜ was founded in 2010, education started in 2012, and the total area of campus area is 3.800.000 square meters [45]. There was no existing building during the foundation period. Adiyaman University was founded, and education started in 2006; the total area of the campus is approximately 1.200.000 square meters [46]. Some educational buildings were formerly part of other universities during the foundation period.

The satellite images were taken from Google Earth with a resolution of 8192-4276. Figures 2-5 show the campus satellite images used for the research from the start period and 2023.



Figure 2. Adiyaman University Campus (2008)



Figure 3. Adiyaman University Campus (2023)



Figure 4. ETÜ Campus (2012)



Figure 5. ETÜ Campus (2023)

3. Results

This section presents the experiment with Chat GPT and Colab cloud application. For every sub-section, the experiments inputs and outputs are first given, then evaluation and discussion are presented in the discussion section.

3.1. Unstructured Conversation with Chat GPT

This conversation was made for ETÜ and Adiyaman University; the total length is 12.000 words and two hours long. The examples from Adiyaman University were given; the details of the steps, codes, and all of the images that Chat GPT generated could not be presented in the text.

(1)Author: I would like a land cover analysis over satellite images. So let me know every step, the method used, and accurate results.

(1)Chat GPT: It explained in detail every step; Step 1: Obtain Satellite Images, Step 2: Preprocess Images, Step 3: Feature Extraction, Step 4: Classification, Step 5: Post-processing, Step 6: Analysis and Results. In addition, it gave example flow and codes for Python and Google Earth Engine.

(2)Author: I will analyze this land cover with you.

(2)Chat GPT: Again, It explained steps for executing the analysis somewhere else.

(3)Author: Show me grassland, construction areas (if possible, distinguish buildings and roads), and water lands. the images have a resolution of 8192-4276, a vertical dimension of 1493,77 m, and horizontal dimension is 2586,53, and an eye level is 2.24 km. (uploaded Figure 3).

(3)Chat GPT: It presented steps and started. Summary of the Process

1. *Image Loading and Visualization:* We loaded the satellite image and visualized it.
2. *Preprocessing:* Applied necessary preprocessing steps.
3. *Initial Segmentation:* Used k-means clustering for unsupervised segmentation.

4. *Manual Labeling:* Manually inspected and labeled each cluster.

5. *Refined Visualization:* Visualized the final classified results.

Figure 6 presents the land cover classification of Chat GPT.



Figure 6. Land use clusters of Adiyaman University

(4)Author: Calculate the area for each land cover.

(4)Chat GPT: Water 44,481.81 m², Construction (Buildings and Roads) 65,705.31 m², Soil/Bare Land 89,579.97 m², Vegetation/Grassland 67,013.02 m²

(5)Author: The satellite image i uploaded is in 2023. I will upload the same place satellite images with the same feature from 2008. Can you compare and mark the differences with a semitransparent hatch? (uploaded Figure 2)

(5)Chat GPT: It presented steps and started. Summary of the Process:

Figure 7 Land Cover Changes from 2008 to 2023 of Chat GPT.

1. *Loaded the Images:* The 2023 and 2008 images were loaded.

2. *Aligned the Images:* Attempted to align the images but faced distortion issues.

3. *Resized and Subtracted:* Resized the images and performed image subtraction to detect changes.

4. *Highlighted Changes:* Applied a semitransparent hatch to highlight the detected changes.

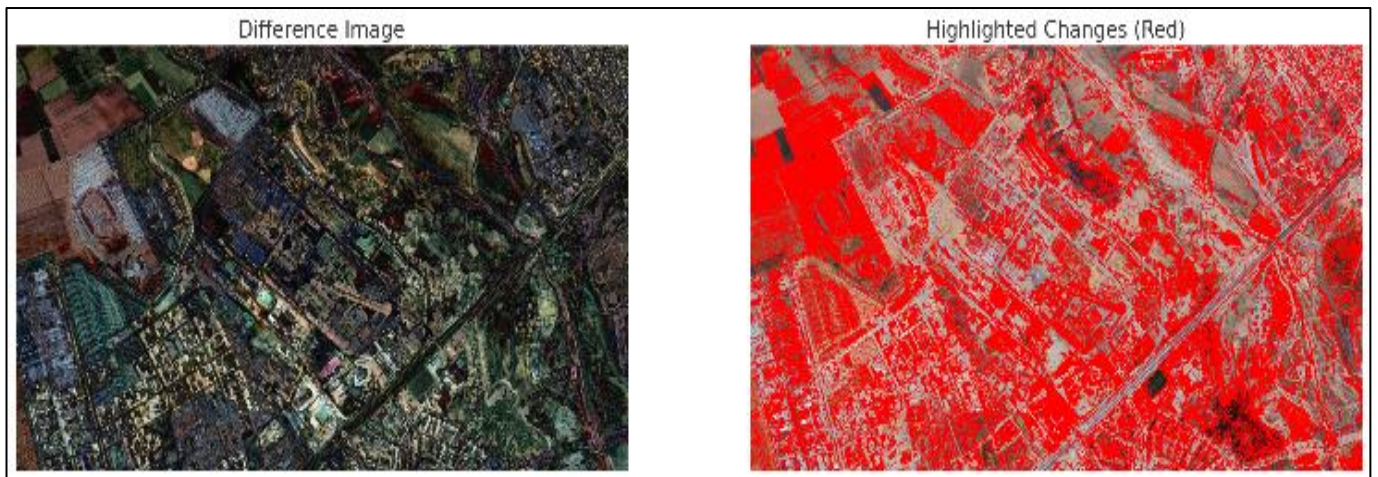


Figure 7. Land Cover Changes from 2008 to 2023 of Adiyaman University

(6)Author: Analyze specific changes in buildings.

(6)Chat GPT: Step-by-Step Implementation

Step 1: *Align and Resize Images*

We have already resized the images. We'll use these resized images for further analysis.

Step 2: *Detect Building Changes* We'll use image processing techniques to detect areas where significant building changes have occurred.

Step 3: *Highlight and Label Changes*

We'll highlight the changes and label them to indicate new constructions and demolitions.

Figure 8 presents the land cover classification of Chat GPT.



Figure 8. Changes in Buildings for Adiyaman University

3.2. Analysis with Chat GPT

This conversation was made for both ETÜ and Adiyaman University; the total length is 8.000 words and has a 1.5-hour duration. The examples from the ETÜ were given, but the details of the steps, codes and all of the images that Chat GPT generated could not be presented in the text. The same process for Adiyaman University was asked from Chat GPT. Due to the limits of the analysis and complexity of Land use results of the unstructured conversation, only imperviousness analysis was asked from Chat GPT to explore the capability of tracking the construction development.

(7)Author: The first image is from 2023, and the second is from 2012. The resolution is 8183*4276, the image's vertical dimension is 1488,70 m, and the horizontal dimension is 2597,64 m. Could we compare the two, showing the constructed areas with a transparent red hatch? (uploaded Figure 4-5)

(7)Chat GPT: Let's compare the two images, detect the constructed areas, and highlight them with a semitransparent red hatch.

Steps:

1. *Load Both Images:* Load the 2023 and 2012 images.
2. *Align and Resize Images:* Ensure both images are aligned and resized.
3. *Detect Constructed Areas:* Use image processing to identify areas where new constructions have appeared.
4. *Highlight Constructed Areas:* Apply a semitransparent red hatch to mark the constructed areas on the 2023 image.

Figure 9 presents the land cover classification of Chat GPT.



Figure 9. Constructed Areas of ETÜ with Comparison

(8)Author: Can you use machine learning for imperviousness comparison?

(8)Chat GPT: Yes, using machine learning, specifically convolutional neural networks (CNNs), can provide more accurate results for detecting building changes. For this task, we can use a pre-trained model or train a custom model to segment buildings from the satellite images.

It explained the steps and codes, then stated, "I cannot run the machine learning code directly in this environment because it requires libraries and models that are not available here. However, I can guide you through the process of segmenting impervious surfaces and comparing their areas using OpenCV and other basic image processing techniques."

(9)Author: Can you do yourself without machine learning?

(9)Chat GPT: I cannot run the machine learning code directly in this environment because it requires libraries and models that are not available here. However, I can guide you through the process of segmenting impervious surfaces and comparing their areas using OpenCV and other basic image processing techniques. Here's how you can achieve this without machine learning:

1. *Load and Resize Images:* Load the 2023 and 2012 images and resize them to the same dimensions.
2. *Segment Impervious Surfaces:* Use thresholding and morphological operations to segment impervious surfaces.
3. *Calculate Impervious Areas:* Calculate the area covered by impervious surfaces in each image.
4. *Compare Impervious Areas:* Compare the calculated areas to determine the change in imperviousness.

I'll execute this step to provide you with the final comparison.

The change in impervious area between 2012 and 2023 is approximately 11,969.18 square meters.

Summary:

- *Impervious area in 2023: 13,140.90 square meters*
- *Impervious area in 2012: 1,171.72 square meters*
- *Change in impervious area: 11,969.18 square meters*

Figure 10 presents imperviousness change from 2012 to 2023 calculated by Chat GPT.



Figure 10. Imperviousness change of ETÜ (Chat GPT)

The reached prompt and process were asked from the Chat GPT for Adiyaman University. Figure 11 presents imperviousness change from 2008 to 2023 calculated by Chat GPT.

The conversation up to this stage was done on 14/15.06.2024. The image analysis, re-analysis, and code generation were available after Chat GPT refused to do analysis and started to generate only codes and explanations of steps to be executed using other platforms. Even if the analysis was asked from Chat GPT in the following three days, it gave similar answers: "It seems there is an issue executing the code in this environment. Let me provide an alternative approach by giving you the code to run on your local machine".



Figure 11. Imperviousness change of Adiyaman University (Chat GPT)

3.3. Analysis with Colab

This conversation was made for both ETÜ and Adiyaman University. The codes and procedure were asked from Chat GPT for the same imperviousness analysis. The same satellite images were uploaded, and codes were copied and run in Colab² environment on 16.06.2024.

(10)Author: Write a code for colab. I will upload two satellite images, which will compare the imperviousness of the two images and highlight the changes in transparent red in first images

(10)Chat GPT: *Certainly! Here's a Colab notebook code to compare two satellite images, calculate changes in impervious areas, and highlight the changes in transparent red on the first image. Also explained the steps;*

1. *Open Google Colab.*
2. *Copy and paste the above code into a new Colab notebook.*
3. *Run each cell step by step.*
4. *When prompted, upload the first satellite image.*
5. *When prompted, upload the second satellite image.*
6. *The resulting image with highlighted changes will be displayed and saved as 'highlighted_changes.png'.*

3-4 four cycles were executed to reach the analysis. The error codes from Colab were asked to Chat GPT, it told the possible code failures and re-generated codes. Finally, the imperviousness change on satellite images was taken and shown in Figure 12-13.



Figure 12. Imperviousness change of ETÜ (Colab)



Figure 13. Imperviousness change of Adiyaman University (Colab)

4. Discussion

² Cloud based services for computing (<https://colab.google/>)

Evaluations were done under two subheadings. First is related to the content and productivity of Chat GPT's responses, and second is related to the content of produced figures for Land Cover and Use Analysis. Table 1 presents the authors' requests during the conversation stages, headings of the outputs, and main evaluations due to the assigned identification number (ID) in the results section.

For ID 1 and 2, it is seen that Chat GPT gave procedure and steps for analysis; however it did not analyze without insisting. It can be stated that Chat GPT platform tries to work by using fewer resources. As mentioned earlier, after some analysis section, it stopped doing analysis and never did again. Calculations of areas produced by Chat GPT were checked manually. They are almost correct; the difference results from converting pixels into metric calculations.

ID 5 is related to comparing two satellite images for land cover changes for different dates. The analysis could be stated as successful; however, the land cover classification was neglected. Further analysis of land cover needs detailed input and code generation. This can also be seen in ID 6, which analyzes only building changes. It is not successful in distinguishing buildings from the other land cover types. In ID 7, a wider analysis was asked, including buildings and constructed areas. The detection could be valid for constructed areas, but grassland is also included.

Table 1. Evaluation of Conversation Sessions

| ID | Request | Output | Evaluation |
|----|--|---------------------------|---|
| 1 | Land Cover Analysis | Steps and Codes | Detailed steps and codes are given |
| 2 | Same Request for 1 | Steps and Codes | Detailed steps and codes are given with forwarding to other platforms |
| 3 | Detailed Request from directly Chat GPT | Analysis and Figure 6 | The analysis needs refinement; however, it has value for the initial process. |
| 4 | Calculation of land cover area | Values | With given dimension information, it converted pixels into area |
| 5 | Land Cover Comparison for two images | Analysis and Figure 7 | Successful disregarding the types of land cover |
| 6 | Changes for building | Analysis and Figure 8 | Unsuccessful in detecting buildings |
| 7 | Constructed areas comparison for two images | Analysis and Figure 9 | Some areas are detected, and there are false detections |
| 8 | Machine learning implementation | Steps and Codes | Libraries and models that are not available |
| 9 | Imperviousness change | Analysis and Figure 10/11 | Successful for general layout |
| 10 | Imperviousness change code request for colab | Steps and Codes | Needs of iteration to get final codes |

Chat GPT can explain the machine learning procedures and codes for image analysis, but the

platform does not allow execution. For ID 9, a more specific and pre-defined analysis is asked. The codes and analysis for the imperviousness procedure are more successful than other land cover analyses. Besides, it can generate the codes for this analysis for execution in Colab. Some iterations were needed to re-generate and correct codes; however, the session was productive since Chat GPT could understand and interpret the error code that Colab gave.

The figures' list, which Chat GPT and Colab produced for satellite image analysis, is given in Table 2. The evaluations are based on manual observation and criticism. Any computational analysis of produced images was not conducted.

In Figure 6, land use clusters are established and presented by Chat GPT. The method is promising; however, the images do not reflect the clusters. It needs refinement by further description of codes and image masking method. Besides, it may need higher resolution images or direct satellite data, including radiation data.

Figure 7 shows the land cover changes, which contain almost every change between two-time sequences. It is very valuable for comparing satellite images to detect changes. However, it does not contain any data for land cover classification, which is very important for any land analysis. Figure 8 shows building changes, tagged as demolished and new buildings. It can be said that defining the building geometry needs more detailed analysis. While analyzing not only the building but also constructed areas, Chat GPT is more successful. The highlighted areas in Figure 9 show most of the constructed areas. The problem was including some grassland. The analysis can be refined by further filtering and masking codes.

Figures 10 and 11 show the promising imperviousness change for ETÜ and Adiyaman University. Except for some vehicle roads, all the land covers were identified in ETÜ. The impervious ratio of the surface cover of service roads may affect this result. Also, in Adiyaman University analysis, the service roads were excluded. Even if some constructed areas cannot be detected, overall performance is liable. Thus, this analysis can analyze the construction development at different times by comparing the other inputs.

Figures 13 and 14 present the same imperviousness change analysis for ETÜ and Adiyaman University, which Colab executed with codes generated by Chat GPT. Although the codes were the same for analysis in Chat GPT and Colab, the results differ. In the ETÜ analysis, the grassland surrounded by service roads was included, and the service roads were identified. In Adiyaman University, service roads and buildings that Chat GPT can not identify were highlighted.

Table 2. List of Produced Figures

| | Content | Produced by | University |
|----------|--------------------|-------------|---------------------|
| Figure 6 | Land Use Clusters | Chat GPT | Adiyaman University |
| Figure 7 | Land Cover Changes | Chat GPT | Adiyaman University |
| Figure 8 | Building Changes | Chat GPT | Adiyaman University |

| | | | |
|-----------|------------------------------|----------|---------------------|
| Figure 9 | Constructed Areas Comparison | Chat GPT | ETÜ |
| Figure 10 | Imperviousness Change | Chat GPT | ETÜ |
| Figure 11 | Imperviousness Change | Chat GPT | Adiyaman University |
| Figure 12 | Imperviousness Change | Colab | ETÜ |
| Figure 13 | Imperviousness Change | Colab | Adiyaman University |

5. Conclusion

Land cover and use identification and analysis over satellite images are valuable procedures to define, analyze, and record urban development. The high-resolution repositories of images and computing methodologies make remote sensing possible for diverse objectives. This research investigates the possible usage of Chat GPT to analyze land cover changes to detect construction development over two university campus examples. The unstructured conversation with Chat GPT was held to learn and identify capabilities, and then land cover/construction areas/imperviousness analysis was asked from Chat GPT. Finally, the analysis was executed in another platform (Colab) with codes generated by Chat GPT. As a bottleneck of the study, it stated that Chat GPT tries to use fewer resources in terms of computing for any analysis. So, further evaluation or experiment could be conducted.

One of the study's findings is the generation and interpreting capability of Chat GPT. It can explain the procedure and steps of the analysis, generate codes, understand the error and failure message, and revise the outputs. Thus, the level of expertise needed for computer codes and steps for land cover analysis is significantly reduced. The problem is that a level of knowledge for evaluating the results and giving feedback to the system is compulsory. The experience shows that superior analysis like land cover classification or building detection needs more training or developed codes. The results are not qualified. Finally, the imperviousness analysis done by Chat GPT and Colab is promising to track the development of campus land. This analysis can be improved by giving needed information to generate codes for filtering or masking diverse land covers.

Author contributions

Sole responsibility

Conflicts of interest

The author declare no conflicts of interest.

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