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Guelta in Saudi Arabia: a Remote Sensing Approach

Omer Alrwais

Information Systems Department, King Saud University, Riyadh 12372, Saudi Arabia

ABSTRACT

Water is the source of life. Identifying small water bodies in rocky terrain (Guelta) becomes important especially in desert regions with limited rain throughout the year. Saudi Arabia has many of these gueltas yet their locations are not entirely known nor the ecosystem surrounding it is sufficiently studied. In this project we have combined GIS with remote sensing to build an automated supervised classifier to identify these gueltas. Before that can be used, the full cycle of data preprocessing and data quality checks were implemented to clean the data. In terms of accuracy of known gueltas, ground truth locations were assessed which revealed 70% of gueltas were correctly classified. Further more, random sampling technique was used for 20 random coordinates, out of which five turned out to be gueltas. Also spectral signature plots were used to study each Guelta independently. In this work we have identified an initial list of Gueltas in Saudi Arabia and designed a dedicated website for it, for others to use and build upon.

Keywords: *Guelta, small water bodies, remote sensing, GIS, supervised classification.*

1. Introduction

A natural phenomenon known as a guelta, is essentially a pocket of water from rainfall found in the upstream of rivers usually in rocky segments of it. It can be found in the Sahara Desert. These channels of water drainage are known as 'wadis', and they are responsible for the formation of these pockets of water. The precise location of these Gueltas is a well-kept secret that is only known to a select group of people who are well familiar with the area in which they are located. There is a possibility of finding Gueltas in regions that are inaccessible to people. These regions have not been investigated by humans to a significant degree.

Saudi Arabia, a country located at the heart of the Arabian Peninsula, suffers from limited natural water supply as about 35% of its 2.15 million km^2 area is desert land. Moreover, average rainfall is less than 150 mm around during the year. On the contrast, pastureland spreads over 79% of the land. This makes identifying surface water of at most importance for grazing, drinking and hunting wild animals. The overall goal of this project is to pinpoint the locations of Guelta areas across the entirety of the Kingdom of Saudi Arabia by using satellite imagery. To the best of our knowledge this is the first study in the region that has focused on geulta identification.

2. Related work

Studies that have used remote sensing methods to study surface water have covered different issues in a multitude of regions ranging from estuarine and wetlands in Yamen [1-2], Gueltas in Mauritania [3], water classification in Algeria [4], surface water monitoring in basins of east Asia [5], rivers of south Africa [6], wetland classification in the Sahara [7], surface water extraction [8-10], temporary surface water mapping in France [11], assessing the quality of surface water in Nepal [12], detecting seasonal water in Mauritania [13] and monitoring surface water in India [14]. While extensive, these studies have not covered gueltas in Saudi Arabia which we believe might be quite different than those found in the sahara region. This study is an extension of the work in [15] where guelta studies were reviewed and in this study we provide the actual implementation of ideas presented in [15].

3. Study are and dataset

The study area includes only Saudi Arabia. Although some known Gueltas in Saudi Arabia are found over mapping platforms such as Google maps or earth, taking that exact location is problematic as it sometimes doesn't pinpoint to the exact Guelta pool as can be seen from figures 1 and 2.

Figure 1: Wrong coordinates

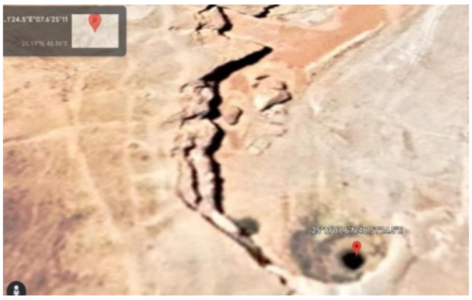

Figure 2: Correct coordinates

To solve this, we have compiled a list of correct Guleta coordinates (ground truth) in SA based on the authors experience and field examination and coordinates acquired from enthusiasts from specialized websites (for example mekshat.com) and the social media (x.com, Instagram, Youtube and snapchat). Later those coordinates were verified over google maps. Table 1 provides some of the used data.

*Corresponding Author: ***Omer Alrwais***

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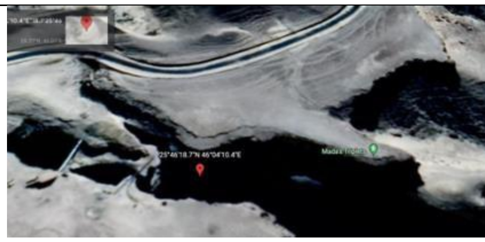
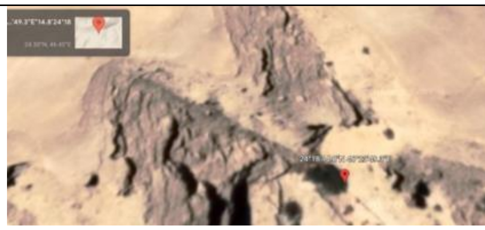
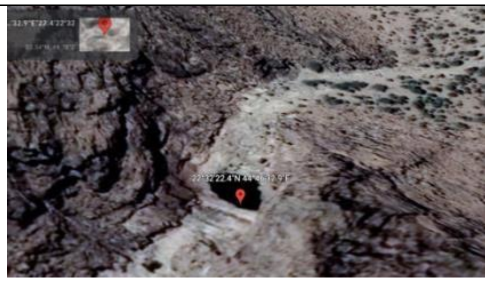
Table 1: Guelta Samples

Name	Area	Coordinates	Image
Ibn daeth	Riyadh	24.66N, 46.50E	
Magbor shaieb	Wadi Nesah	24.12N, 46.48E	
Thabaheh	Malham	25.18N, 46.21E	
Selheah	Rawdat Al Khafs	25.59N, 46.42E	
Um gledah	Tumair	25.77N, 46.07E	
Saieadh	Al-Muzahmiya	24.30N, 46.40E	
Jadah	Hasat Al Dab	22.54N, 44.78E	

After that, we had to choose the date that the satellite images will be retrieved from. In order to have the most visible images of gueltas with water, we chose images within one week of periods of heavy rain between 2022 and 2033 as shown in table 2.

Table 2: Sample of heavy rainfall for each weather station in Saudi Arabia between 2022 and 2023

Name	Coordinates	Date of Rainfall
Riyadh	24.7136° N, 46.6753° E	26-03-23
Al Haeer	24.4044° N, 46.8396° E	26-03-23
Irqah	24.6872° N, 46.5824° E	26-03-23
Diriyah	24.7481° N, 46.5363° E	26-03-23
Al Uyaynah	24.9018° N, 46.3865° E	26-03-23
Al-Kharj	24.1576° N, 47.3248° E	13-03-23
Ad-Dilam	23.9766° N, 47.1557° E	13-03-23

The next step was to choose the satellite type to obtain images, we went with Sentinel 2 satellite. The multispectral imager aboard Sentinel-2 satellites encompasses numerous bands throughout the electromagnetic spectrum. The Sentinel-2 satellites are capable of capturing data across 13 distinct spectral bands. These bands encompass different regions of the electromagnetic spectrum, enabling the detection of diverse surface characteristics on earth. The Sentinel-2 satellites' spectral bands furnish an abundance of data that is utilized in a multitude of applications, including but not limited to agriculture, land cover classification, ecological monitoring, and disaster management.

Gueltas, which are geological formations prevalent in specific arid regions. They denote water pockets that are frequently discovered in arid climates, these formations may serve as an essential water source for human populations and animals alike. A guelta's size can vary substantially. Gueltas can range in size from small water pockets to bigger, more widespread pools, depending on geological formations, water sources, and local environmental conditions. Some gueltas, on the other hand, may only store a few cubic meters of water, forming small, isolated pools. These smaller gueltas may be only a few meters in diameter and depth. Bigger gueltas, on the other hand, can span a bigger area and hold greater amounts of water. They can be several meters in diameter or hundreds of meters across, with deeper pools capable of holding a large amount of water, especially during rainy seasons or when fed by groundwater sources. Utilizing all Sentinel-2 bands for guelta classification can be advantageous because to the extensive spectral information available across several wavelengths. Every band acquires distinct data regarding the Earth's surface, and integrating all bands can augment the precision and resilience of categorization systems.

The following Sentinel-2 bands were used for classifications:

1) Band 2: This band encompasses the blue spectrum and potentially aids in differentiating aquatic environments from adjacent land.

2) Bands 3 and 4: Correspond to the red and near-infrared wavelengths. The identification of these bands is imperative in the classification of guelta owing to their spectral characteristics and the data they provide.

3) Bands 5, 6, and 7: The red edge bands exhibit sensitivity to variations in the chlorophyll content of vegetation.

4) Band 8 and Band 8A: Water absorbs significantly in the near-infrared portion of the spectrum, making near-infrared bands useful for distinguishing water bodies from other features.

5) Bands 11 and 12: Water sensing can benefit from shortwave infrared bands because of the water's specific absorption characteristics at these wavelengths.

Bands 1 and 9, which correspond to the visible and shortwave infrared spectra, respectively, acquire data. Although remote sensing methods contribute to the overall comprehension of the landscape and hold significance in this regard, they may not be as directly applicable to the precise classification of guelta. The Sentinel-2 mission utilizes Band 10, which is designated as the Shortwave Infrared (SWIR) band, the region of the shortwave infrared spectrum contains information that is useful for a variety of remote sensing applications. Nevertheless, when considering the classification of guelta, Band 10 may possess restricted practical utility. Later on, OpenStreetMap tiles were added to enhance visualization.

3.1 Data preprocessing

Preprocessing is necessary even when the image has undergone atmospheric correction, in order to convert pixel values to a decimal value of reflectance. Automatic conversion to reflectance is possible. The metadata file, which is a text file named "MTL" and is downloaded alongside the images, which comprises the necessary data for the conversion process. To obtain reflectance values for bands, the Preprocessing module in QGIS was used by selecting the preprocessing button from the SCP menu or dock and navigate to the Sentinel-2 tab. The selection of bands is loaded into the Metadata table automatically. To initiate the conversion procedure, the directory containing the converted bands were selected and the RUN button was clicked. Converted bands (filename beginning with RT_) are loaded and displayed after a brief delay of a few minutes. All bands stored in QGIS layers may be removed, with the exception of those whose names commence with RT_.

3.1.1 Reproject And Clean The Data

Global datasets are occasionally distributed in tiles with distinct UTM zones. This subsection demonstrates how to combine them into a single mosaic using QGIS and a GDAL batch script. A batch script was executed to reproject the tiles to a geographic coordinate system utilizing the gdalwarp function as shown in figure 3. Subsequently, a QGIS virtual raster was constructed as shown in figure 4.

```
for %%f in (*.tif) do (
   echo %%~nf
   gdalwarp -t_srs EPSG:4326 -dstnodata 0 %%f .\%%~nf_gcs.tif
)
```

Figure 3: reprojection script

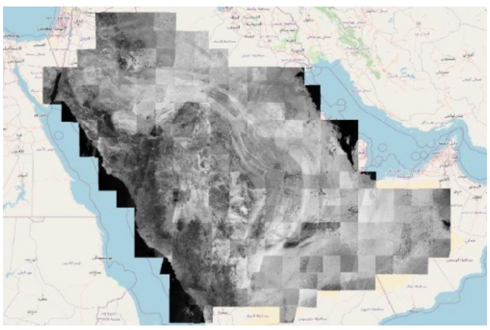


Figure 4: Band 12 reprojected and cleaned.

3.1.2 Create a virtual raster

A new raster file is generated when rasters are merged, which duplicates the data. This procedure requires additional hard drive space. Without the necessity of creating a new raster file, which could be quite large in size. It's possible to instead establish a Virtual Raster. Frequently referred to as a Catalog, this term effectively describes its purpose. It is not an entirely novel raster. Instead, it is a method for arranging the current rasters into a single catalog, or file, to facilitate access. The output is shown in figure 5.

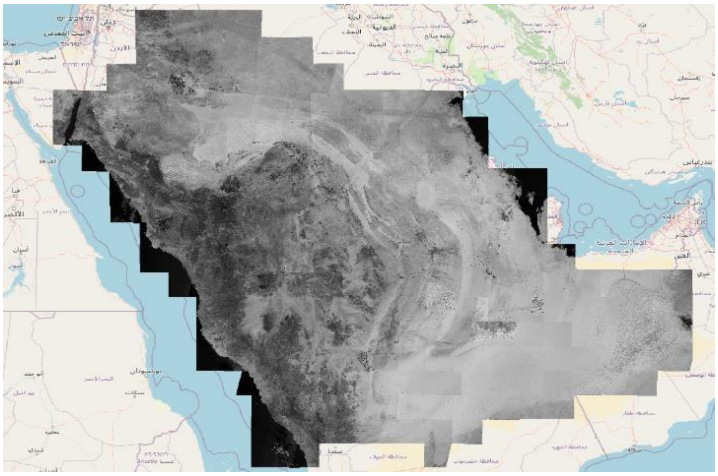


Figure 5: Band 12 virtual raster

Merging the data does not generate an entirely new raster file for a VRT. In contrast, it generates a catalog or virtual mosaic of the input rasters so as to prevent the duplication of the pixel values. While a VRT file may contain metadata and references to the locations of the source raster files, it does not replicate or combine the pixel values into a distinct file. Multiple raster files ought to be dealt with as a single dataset to prevent data duplication, and large datasets needed to be managed more efficiently without requiring additional disk space. VRTs were therefore implemented.

3.1.3 Clip the data

An approach to minimizing processing time and restricting the study area is to crop the image. Before anything else, a Band set comprising the bands to be clipped must be defined. The Band sets, comprising numbered collections of raster bands and associated data (including center wavelength and acquisition date), are utilized by multiple tools within SCP. Bandset is accessed via the SCP dock or the SCP menu by selecting the bandset tool button. To update the layer list, the following bands: 2, 3, 4, 5, 6, 7, 8, 8A, 11, and 12 are selected. To add the selected rasters to Band set 1, the plus button is clicked. To specify a directory in which clipped bands are to be stored, the RUN button should be clicked. When the Output name prefix is specified, new files will be generated with that prefix. Upon the completion of the procedure, clipped rasters will be loaded and visually presented as shown in Figure 6.

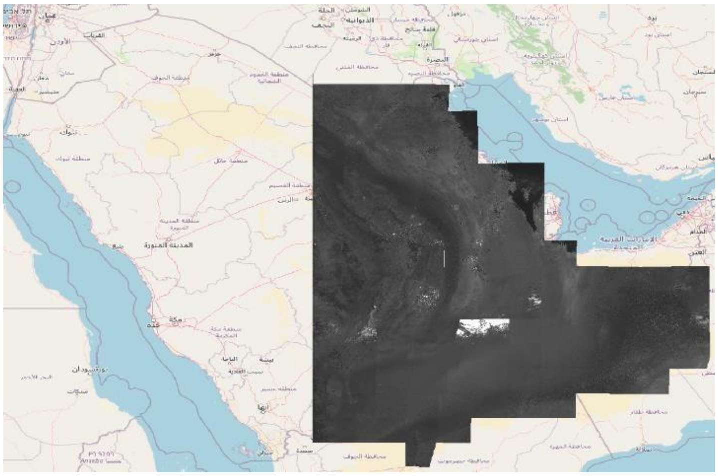


Figure 6: Band 2 Clipped

3.1.4 Generate the input file for training

The Band set, which serves as the input image for SCP classification, must now be defined. To access the Bandset tab, select the Bandset tool button from the SCP menu or dock. The "Reset" button in the Band set definition is utilized to remove all bands from the active band set that was created in the preceding steps. To refresh the layer list and ensure that all converted bands are selected, the reload button is clicked. To add the selected rasters to the Band set, a plus sign is then used. Arrange the band names in ascending order in the table Band set definition (clicking "order by name" will automatically arrange bands by name). In conclusion, the Wavelength quick settings menu is utilized to select Sentinel-2, which automatically configures the wavelength unit and center wavelength of each band, which are essential for the calculation of spectral signatures as shown in figure 7.

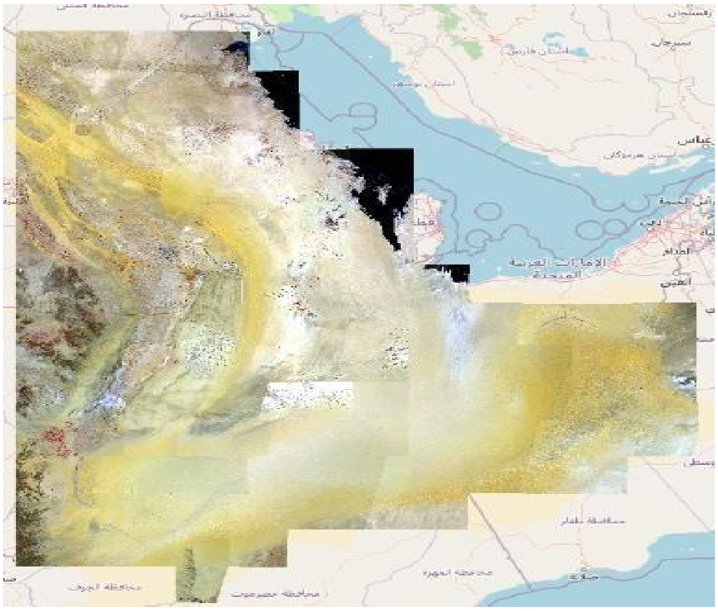


Figure 7: Bands 7-3-2 in order of RGB

Color composites of bands can be displayed as follows: In order to access the Near-Infrared, Red, and Green regions, the item 7-3-2 (which corresponds to the band numbers in the Band set) is selected by clicking the RGB= list in the Working toolbar. The map's image colors exhibit variation in accordance with the bands that are selected; vegetation is denoted by the color red; had the 3-2-1 option been chosen, natural colors would be presented. A temporary virtual raster (referred to as Virtual Band Set 1) is automatically generated when a band set is specified, enabling the implementation of color composite. To accelerate the visualization process, it is possible to conceal all layers within the QGIS Layers and only display the virtual raster. At this moment, in order to collect Training Areas (ROIs) and compute their Spectral Signatures (which are utilized in classification), it is necessary to generate the Training input. To generate the Training input, which is assigned a name such as training.scp, one selects the Training input tab in the SCP dock and clicks the "New File" button. A vector with the same name as the Training input is appended to QGIS layers, along with the file path.

3.1.5 Establishing region of interest (ROIs)

ROIs will be generated through the definition of classes and macroclasses. A ROI is designated to a specific land cover class by means of a Macroclass ID (MC ID), which is allocated to each ROI via a Class ID (C ID). Macroclasses consist of numerous materials with distinct spectral signatures; to attain accurate classification outcomes, it is necessary to distinguish the spectral signatures of distinct materials, even if they are members of the same macroclass. Thus, multiple ROIs will be generated for each macroclass, with each ROI being assigned a unique C ID while maintaining the same MC ID. The manual creation of a polygon or the implementation of an automatic region-growing algorithm can both generate ROIs. A water body is depicted as a dark blue area that is magnified on the map. To generate a manual ROI within the dark area, one must select the manual ROI icon from the Working toolbar.

The image is layered with a temporary orange semi-transparent polygon, which is not retained in the Training input. The temporary polygon can be saved to the Training input if its shape is satisfactory. Opening the Training input permits the definition of Classes and Macroclasses. With MC ID = 1 and MC Name = Water in the ROI & Signature list, C ID = 1 and C Name = Guelta are also specified. At this point, the ROI is saved in the Training input by clicking Save ROI. The ROI is added to the ROI & Signature list and the spectral signature is computed after a brief interval of time (since the Signature checkbox is selected). The C ID in the ROI & Signature list is evidently incremented by one. The saved ROI is visually represented on the map as a dark polygon, while the transient ROI is eliminated. Additionally, the Type of RS in the ROI & Signature list indicates that the ROI spectral signature was computed and stored in the Training input. The ROI for the remaining classes will now be created.

4. Data processing procedure

The processing was performed using QGIS 3.4 software and the Semi-Automatic Classification (SCP) plugin for classification. To extract Guelta from Saudi Arabia using the SCP (Semi-Automatic Classification Plugin) in QGIS, the following approach depicted in Figure 8 was used.

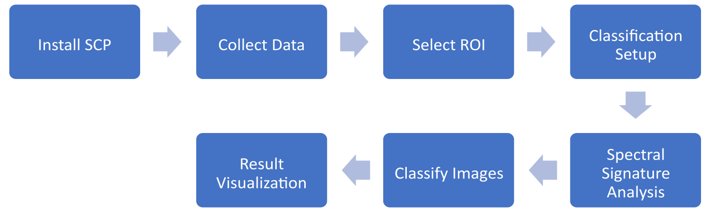


Figure 8: Processing steps

- **SCP Plugin Installation:** Ensure that the SCP plugin is installed in QGIS, if it is not already.

- **Data Acquisition and Preparation:** Obtain satellite imaging data of Saudi Arabia. Perform image preprocessing to improve the overall quality if deemed required.

- **Region of Interest (ROI) Selection:** Specify the geographical boundaries within Saudi Arabia where gueltas are anticipated to exist.

- **Setup for Classification:** Select training samples for the classes of interest, specifically for gueltas, within the chosen study region. Utilize SCP technologies within QGIS to establish a classification framework to classify the imagery.

- **Spectral Signature Analysis:** Utilize SCP techniques to examine the spectral signatures of the observed gueltas and nearby characteristics. Conduct an analysis of the spectral properties of gueltas through the extraction and examination of their spectral signatures from satellite imagery. The comprehension of these distinct spectral patterns facilitates precise classification.

- **Images Classification:** Utilize the selected classification technique to analyze the complete satellite image. Create a classification map that differentiates gueltas as a separate class or category. Supervised classification can be achieved by utilizing the techniques provided by the SCP plugin integrated into QGIS. Maximum Likelihood Classification is an example of an algorithm that can be utilized to classify imagery into various land cover classes, including gueltas. In this project, classification by minimum distance was applied.

- **Interpret the outcome:** Display and map the extracted gueltas utilizing QGIS and SCP visualization tools. By generating statistics and overlays from the classified results, interpretation and analysis are enhanced.

5. Classification approach

Classification algorithms employ spectral signatures to identify image pixels. Diverse substances may exhibit comparable spectral signatures, particularly when multispectral images are taken into account. Pixels may be incorrectly classified if the spectral signatures employed for classification exhibit excessive similarity, rendering the algorithm incapable of accurately differentiating said signatures. Assessing the Spectral Distance between signatures is therefore advantageous for identifying similar spectral signatures that necessitate elimination. Obviously, the definition of distance differs depending on the classification algorithm in use. By displaying a signature plot, spectral signature similarity can be easily evaluated. The subsequent diagram in Figure 9 illustrates the signature plots of various materials.

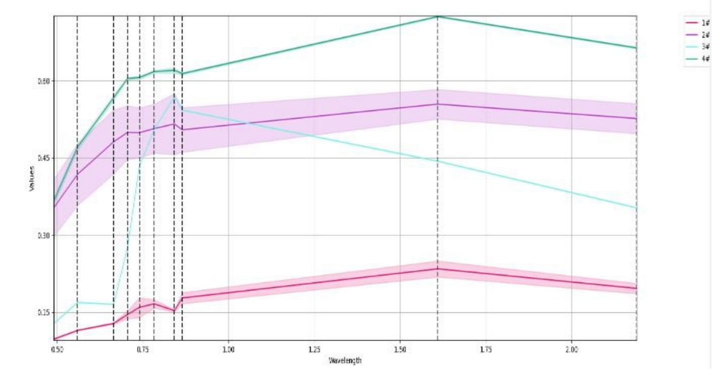


Figure 9: Spectral signatures plot

The plot displays the signature line. Additionally, it illustrates the spectral range, including the minimum and maximum values, of each band through a semi-transparent region colored similarly to the signature line. The process of classification depends on the spectral signatures of the acquired ROIs. Before the final classification, it is beneficial to generate a Classification Preview so that the results (which are influenced by spectral signatures) can be evaluated. Figures 10 and 11 illustrates classification preview. If the results are unsatisfactory, additional ROIs can be gathered to improve land cover classification.

Figure 10: Before

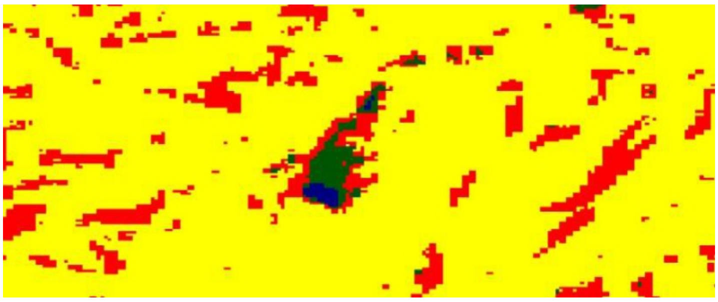


Figure 11: After

At this time, the classification algorithm must be chosen. The minimum distance classification algorithm is a direct approach utilized in tasks involving pattern recognition and classification. When contemplating the classification of geological formations such as gueltas, the implementation of minimum distance classification can yield numerous advantages:

1. Simplicity: The minimum distance classifier possesses a relatively straightforward implementation and comprehension. It assigns the data point to the class whose centroid is closest to it after calculating the distance between the point and the class centroids.

2. Appropriateness for Gueltas Classification: Gueltas may possess discernible characteristics across multiple dimensions, including but not limited to size, depth, geological composition, and adjacent vegetation. A minimum distance classification algorithm may be appropriate in situations where the aforementioned features are quantified, thereby enabling precise distance measurement.

If classification previews yielded satisfactory results (pixels were appropriately designated to the classes specified in the ROI and Signature list), the complete image can be classified in terms of land cover. As can be seen in figure 12.

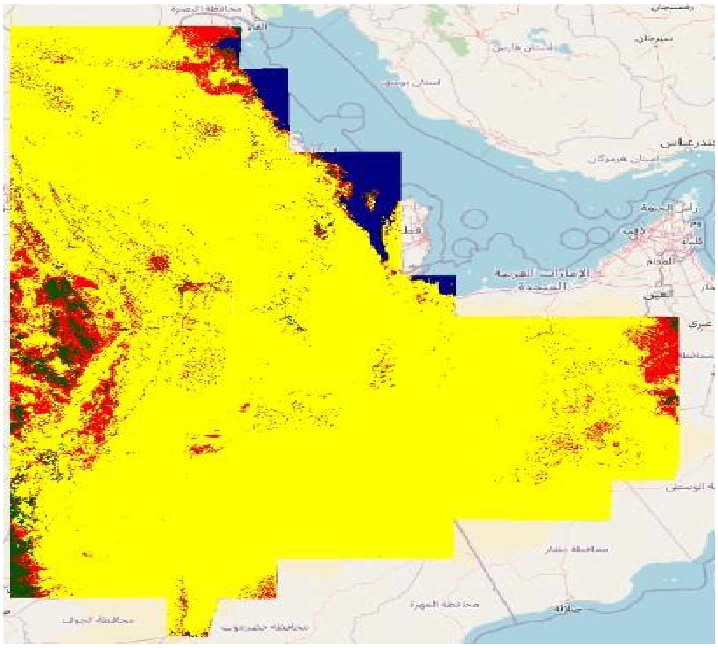


Figure 12: Output

After classification, raster to vector transformation was performed along with feature extraction for each polygon in order to conduct targeted analyses or refine data to concentrate on particular geographic regions or features that are of interest.

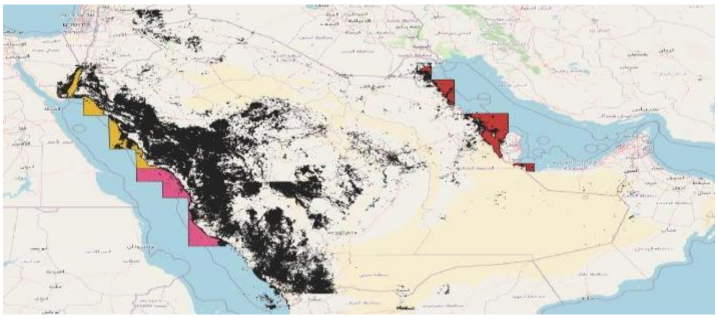


Figure 13: Extracting water features

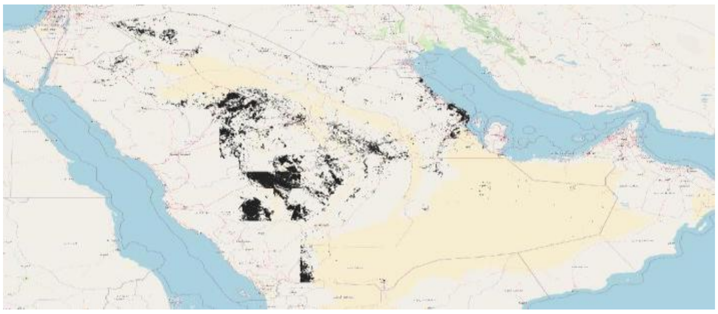


Figure 14: Deleting all non-guelta water features

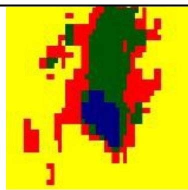
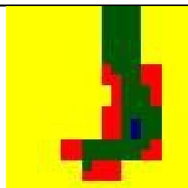
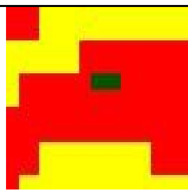
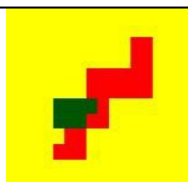
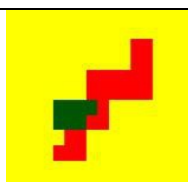
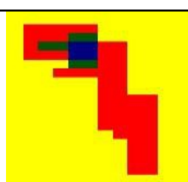
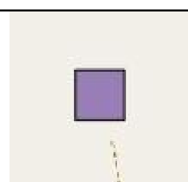
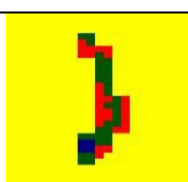
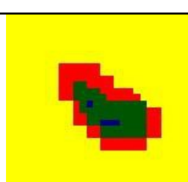
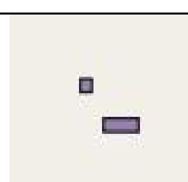
In Figure 13 and 14 most water features situated outside of Saudi Arabia and those not in an arid region were excluded.

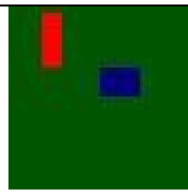
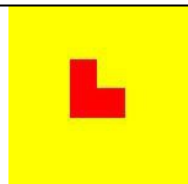
6. Evaluation of results

Random sampling technique was utilized from the dataset comprising classified data and subsequently validating the correspondence of these arbitrarily chosen points with gueltas via Google Maps may serve as a practical approach to assess the

classification outcomes. Moreover, spectral signature visualization is utilized in the testing and evaluation procedure. The utilization of spectral signature visualization is crucial for the comprehension of guelta spectral response patterns, as it provides a comprehensive understanding of their unique attributes. By employing this method, a comparative analysis can be conducted between the dataset and known features or ground truth data. This enables the detection of anomalies or inconsistencies and significantly contributes to the validation and improvement of the classification process.
First accuracy of detection was validated by comparing it to known Guelta locations (ground truth). This allows for the assessment of the accuracy of the satellite image evaluation. Table 3 depicts some of the validation performed.

Table 3: Accuracy validation

Name	Raster	Polygon	Coordinates
Ibn daeth			24.66N, 46.50E
Magbor shaieb			24.12N, 46.48E
Thabaheh		-	25.18N, 46.21E
Selheah		-	25.59N, 46.42E
No known name		-	25.59N. 46.42E
Um gledah			25.77N, 46.07E
Ftekah			24.97N, 46.00E
Saieadh			24.30N, 46.40E

Jadah			22.54N, 44.78E
Mestethal		-	25.19N, 46.86E

A random sample technique was employed to select data points from the classified dataset. These randomly selected points were then cross-referenced with Google Maps to evaluate if they accurately represent gueltas. This method can be valuable for assessing the accuracy of the classification results. This method offers a way to verify the precision of the classification algorithm by comparing it to real-world observations. Nevertheless, it is crucial to take into account some aspects that may result in inconsistencies during the verification process:

1. Ground Truth Data Quality: The precision of Google Maps or any other external source utilized as ground truth may not always be flawless. Inaccuracies or obsolete data in the reference information can result in inconsistencies between the classified data and the verification process.

2. Sampling Bias: The random selection of data may lead to a distorted portrayal of the dataset due to bias. The sampled data may be biased due to an overrepresentation or under representation of certain areas or types of gueltas, which can impact the overall assessment.
The code in figure 15 was used to randomly chose 20 coordinates. This code use Python's random module to generate a sequence of 20 random numbers ranging from 1 to 439,396. The sort() method is utilized to rearrange the components of the random numbers list in ascending order. The sorted sequence of randomly generated numbers will be displayed in table 4.

```python
import random

# Generating 20 random numbers between 1 and 439396
random_numbers = [random.randint(1, 439396) for _ in range(20)]

# Sorting the generated random numbers in ascending order
random_numbers.sort()

# Printing the ordered random numbers
print(random_numbers)
```

```
[13328, 77274, 112586, 123772, 125287, 201820, 215178, 234181, 236584, 281292,
296284, 321510, 329884, 366266, 379049, 387961, 400104, 412416, 422430, 434735]
```

Figure 5: Random sampling script

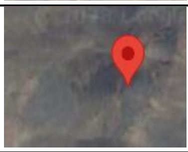
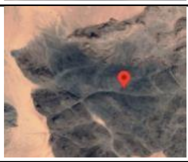
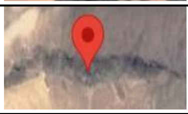
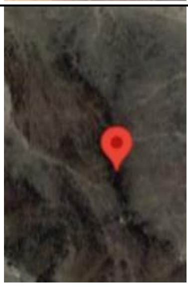
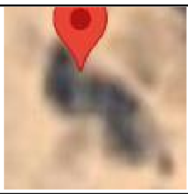
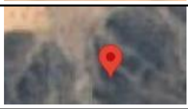
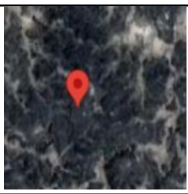
Although the main purpose of the Semi-Automatic Classification Plugin (SCP) is to aid in the processing, classification, and analysis of remote sensing data, specifically satellite imagery, distinguishing between lakes and gueltas can be difficult for a variety of reasons:
1. Spectral similarity: Lakes and gueltas can display comparable spectral properties in satellite imaging, particularly under specific environments. Both aquatic environments can exhibit similar patterns of reflectance in remote sensing bands, which poses a challenge in distinguishing them merely based on spectral signatures.

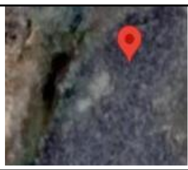
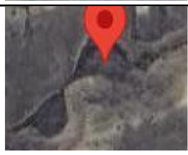
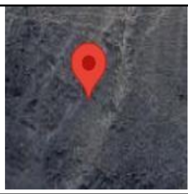
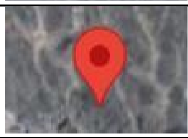
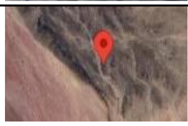
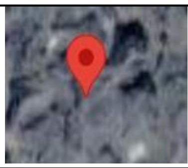
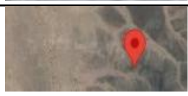
2. Resolution and Scale: Satellite imaging may lack the requisite level of precision to differentiate tiny water bodies such as gueltas from bigger ones such as lakes. The identification of minor water features may be hindered by lower resolution or scale constraints in the images.

3. Algorithm Limitations: SCP's classification algorithms may lack specialized attributes or customized procedures designed for distinguishing the distinct properties of lakes and gueltas. The algorithms employed in SCP may not provide priority to distinguishing these specific water characteristics.
4. User Proficiency and Interpretation: The accurate identification and distinction between lakes and gueltas can greatly depend on the user's proficiency in interpreting spectral signatures, comprehending local conditions, and manually improving classification outcomes, which may not be fully automated in SCP.
In general, the difficulty in distinguishing between lakes and gueltas using SCP mostly stems from the difficulty of identifying these bodies of water purely based on the spectral information obtained from satellite images. In addition to specialized algorithms, higher-resolution imagery, and manual interpretation, this task frequently surpasses the capabilities of automated classification modules such as SCP.

Table 4: Random sampling

Random #	Image	X Coordinates	Y Coordinates
13328		44.22354E	26.15333N

77274		39.19762E	30.70433N
112586		41.02524E	27.00653N
123772		40.55312E	26.85566N
125287		42.50563E	26.83953N
201820		43.62874E	23.62666N
215178		43.15177E	23.35372N
234181		43.87776E	23.13628N
236584		42.2895E	23.1113N
281292		42.28166E	21.77074N
296284		42.24315E	21.70009N
321510		42.26011E	21.58941N
329884		42.00311E	21.55623N

366266		42.42798E	21.38469N
379049		41.97557E	21.31829N
387961		43.84099E	21.23658N
400104		42.30078E	21.14091N
412416		42.10191E	21.07047N
422430		42.2742E	21.01205N
434735		42.47271E	20.81279N

The application of spectral signature plots was crucial to this assessment. Spectral signature plots facilitated the validation process by offering a graphical depiction of the distinct spectral reactions exhibited by gueltas. The examination of these spectral patterns enabled the discernment of particular attributes, thereby improving the credibility of classification outcomes and augmenting comprehension of the gueltas' spectral behavior.

7. Conclusion

A guelta is a type of wetland that can be found in arid regions and is created when underground water in lowland depressions overflows and creates permanent pools and reservoirs. Gueltas are hidden from view by a canyon. The enormous sandstone cliffs that surround this area serve to protect its waters. One is able to map the size of a Guelta or foretell where water would flow after strong storms by using a Geographic Information System (GIS), which is an extremely useful tool for appraising a region. It is necessary to make a decision as to the location of surface water in the Kingdom of Saudi Arabia because this has an effect on the management of domestic water in many aspects. Satellite imagery can be used to determine the surface water areas of a region. The goal of this work was to identify all Guelta regions that are located within the Kingdom of Saudi Arabia.

Data is becoming an increasingly important component of urbanized city administration as a means of both enhancing the decision-making process and shortening the amount of time needed to arrive at a decision. Machine learning, geospatial analysis, and artificial intelligence are some of the areas that might be implemented into the system to better data analysis and management. These are just few of the domains. Alternately, these data can be utilized to increase the automation of the system by identifying Guelta regions, and the system could automatically draw the optimal path in real-time based on satellite-derived traffic routes. This would be possible if the system had access to satellite imagery.

One further tactic for attaining growth is to work toward elevating the standard of the information that is compiled and analyzed. Databases can be improved and kept up to date so that they combine occurrences from the present with those from the past in order to make data analysis more effective. Since both spatial and nonspatial data can be stored inside a GIS's systems, the Geographic Information System (GIS) plays an important role in the process of centralizing data. It is vital to select key datasets in order to increase the quality of the study. Additionally, it is required to determine how to combine multiple datasets in order to have a functional influence on the entire project.

To achieve a greater level of accuracy, it is recommended to take into consideration the enhancement of classification algorithms, the acquisition of imagery with a higher resolution, the execution of further preprocessing, the incorporation of more features into the classification process, and the testing of the classification findings using different ground truth datasets or methodologies. In order to properly interpret and resolve any disparities that may exist between the classified findings and the ground truth observations, it is necessary to be aware of the limitations imposed by both the ground truth data and the classification technique.

When imagery from satellites are analyzed, it may be feasible to differentiate between lakes and gueltas by employing additional image processing techniques and algorithms that have been developed expressly for the detection and categorization of water bodies. These methods might include the following:

1. This technique examines the surface qualities of lakes and gueltas by taking into consideration their contextual surroundings and appearance in satellite imagery. Texture analysis is the first technique.

2. Classification and Machine Learning: In order to differentiate between lakes and gueltas based on the attributes that are obtained. This is done in order to solve classification difficulties.

In general, the adoption of technology, analysis, modeling, and display of results are not possible without the presence of hardware components. As a result, the government has the ability to make investments in highly advanced and fully functional computers, which will improve the system for the collection, analysis, and effectiveness of data. In these kinds of circumstances, locals may have access to highly effective smart devices that shorten the amount of time needed for a response and enable quicker system access. The use of efficient gadgets also enables rapid and insightful studies, which provide locals with guidance on the most expedient routes to take. A key feature is the potential improvement that mobile mapping, photography, and data collection in real time may have on emergency response.
It is of the utmost importance to acknowledge some of the constraints that were encountered during the course of this work. These constraints include the limitations that were imposed on the enormous amount of data that needed to be reprojected and clipped, computation, and the inherent challenges that were encountered when identifying gueltas from other natural features that were similar. The existence of these limitations highlights the importance of continuously validating and improving methodologies in order to achieve higher levels of precision and dependability. The findings of this research, on the other hand, propose major contributions to the management of resources, and the monitoring of environmental conditions in regions that are dependent on these natural water reserves. Through the provision of a fundamental framework for future research, the established technique makes it easier to make sustainable use of gueltas and to preserve them in regions where water is of limited availability.

References

1. Al-Mahfadi, A.S., Dakki, M., Alaoui, A. et al. Classification of Estuarine Wetlands in Yemen Using Local and Catchment Descriptors. Estuaries and Coasts 44, 1946–1974 (2021).

2. Al-Mahfadi, Afrah & Dakki, Mohamed. (2020). Scientific elements for a Yemeni wetland conservation strategy: overview of the main factors explaining the diversity and characteristics of wetlands. Bulletin de l'Institut Scientifique. 42. 31-42.

3. Vale, Cândida & Pimm, Stuart & Brito, José. (2015). Overlooked Mountain Rock Pools in Deserts Are Critical Local Hotspots of Biodiversity. PloS one. 10. e0118367. 10.1371/journal.pone.0118367.

4. KECHAIRI, R. (2021). SOURCES OF WATER COMPENSATION OF THE ARGAN GROVE Argania spinosa L. IN ALGERIAN WESTERN SAHARA. Algerian Journal of Arid Environment "AJAE", 11(1), 8-8.

5. Markert, Kel & Chishtie, Farrukh & Anderson, Eric & Saah, David & Griffin, Robert. (2018). On the merging of optical and SAR satellite imagery for surface water mapping applications. Results in Physics. 9. 10.1016/j.rinp.2018.02.054.

6. Seaton, Dylan & Mazvimavi, Dominic. (2020). Use of multi-temporal satellite data for monitoring pool surface areas occurring in non-perennial rivers in semi-arid environments of the Western Cape, South Africa. ISPRS Journal of Photogrammetry and Remote Sensing. 167. 375-384. 10.1016/j.isprsjprs.2020.07.018.

7. El Fellah, Bouchta & Dakki, Mohamed. (2020). River'snatural reservoirs: new inputs to the classification of Mediterranean and Saharan wetlands. Bulletin de l'Institut Scientifique. 42. 1-14.

8. Lasko, Kristofer & Maloney, Megan & Becker, Sarah & Griffin, Andrew & Lyon, Susan & Griffin, Sean. (2021). Automated Training Data Generation from Spectral Indexes for Mapping Surface Water Extent with Sentinel-2 Satellite Imagery at 10 m and 20 m Resolutions. Remote Sensing. 13. 4531. 10.3390/rs13224531.

9. Papa, Fabrice & Frappart, Frédéric. (2021). Surface Water Storage in Rivers and Wetlands Derived from Satellite Observations: A Review of Current Advances and Future Opportunities for Hydrological Sciences. Remote Sensing. 13. 4162. 10.3390/rs13204162.

10. jiang, wei & He, Guojin & Long, Tengfei & ni, yuan & Liu, Huichan & Peng, Yan & Wang guizhou, Wang guizhou. (2018). Multilayer Perceptron Neural Network for Surface Water Extraction in Landsat 8 OLI Satellite Images. Remote Sensing. 10. 10.3390/rs10050755.

11. Bioresita, F & Puissant, Anne. (2021). Rapid mapping of temporary surface water using Sentinel-1 imagery, case study: Zorn River flooding, Grand-Est, France. IOP Conference Series: Earth and Environmental Science. 731. 012031. 10.1088/1755-1315/731/1/012031.

12. KC, A. & Chalise, Ashish & Parajuli, Devraj & Dhital, N. & Shrestha, Saloni & Kandel, T.. (2019). Surface Water Quality Assessment Using Remote Sensing, Gis and Artificial Intelligence. Technical Journal. 1. 113-122. 10.3126/tj.v1i1.27709.

13. Campos, João & Sillero, Neftalí & Brito, José. (2012). Normalized difference water indexes have dissimilar performances in detecting seasonal and permanent water in the Sahara – Sahel transition zone. Journal of Hydrology. 465. 438-446. 10.1016/j.jhydrol.2012.07.042.

14. Bhangale, Ujwala & More, Swapnil & Shaikh, Tanishq & Patil, Suchitra & More, Nilkamal. (2020). Analysis of Surface Water Resources Using Sentinel-2 Imagery. Procedia Computer Science. 171. 2645-2654. 10.1016/j.procs. 2020.04.287.

15. Alrwais, Omer. Determining Temporary Small Water Bodies Via Remote Sensing: The Case of Guelta. FOURRAGES, (2023).

