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*Original Article*

# A Comparative Study on Pixel-based Classification and Object-Oriented Classification of Satellite Image

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***Abstract*** - *Artificial intelligence is advancing rapidly in automatically recognising features from satellite imagery. Satellite imagery is of great interest to the computer science community, which seeks to give machines the ability to recognize their environment by classifying satellite images. This type of processing has shown great potential for monitoring large areas at a relatively low cost. Remote sensing and, in particular, satellite imagery provide Earth observation data that are collected, analyzed, and processed for civil and military purposes. They offer many possibilities for mapping and monitoring urban areas. Indeed, the analysis and classification of satellite images have many applications in meteorology, oceanography, fisheries, agriculture, biodiversity, geology, cartography, land use planning, warfare, etc. In this paper, we focus on satellite image classification, which is based on different algorithms belonging to different approaches that differ in terms of accuracy and quality of results. Hence, we propose in this paper to provide a comparative study of these approaches in terms of their algorithms and techniques, image resolutions, and image types and will show and discuss their strengths and weaknesses. In this comparative study, we will introduce each approach, select a set of comparison criteria, and apply a comparative methodology to obtain results. The methodology we have chosen for this purpose is WSM (Weighted Scoring Model), which corresponds to our needs. Indeed, this method allows us to assign a weight to each of our criteria to calculate a final score for each of our compared methods. The results obtained reveal the weaknesses and strengths of each of them and open opportunities for their future improvement.*

***Keywords*** **-** *Computer vision, Remote sensing, Satellite image, WSM weighted, Classification.*

## 1. Introduction

Satellite data are consistent over large areas and time and provide information at various geographic scales. Information derived from remote sensing can help describe and model the urban environment, providing a better understanding of the benefits of applied urban planning and management [1]. A report published by NASA highlighted that advances in satellite-based land surface mapping contribute to more detailed urban maps, allowing planners to understand better the dynamics of urban growth and sprawl and related land management issues [2].

Satellite image classification plays an important role in remote sensing. It is one of the most common information extraction techniques. It is challenging as it relies on many different approaches and methods that can be applied depending on seasonal and environmental conditions [3].

D. Jawak and al [4] state that classifiers for extracting information from satellite images are based on three types of classification: Supervised, unsupervised, and convolutional neural network or CNN classification. These classification methods fall into two approaches: pixel-based classification and object-oriented classification [3].

This paper compares these algorithms using the weighted scoring model (WSM). We start our comparative study by extracting the most relevant criteria for the comparison and justifying our choice for each criterion. Then, we define the WSM method before assigning weights to each criterion and obtaining final scores for the satellite image classification methods and techniques. The objective of this spider graph is to show us the best classification approach according to a set of scores for each criterion, such as high resolution spatial, spectral, segmentation, etc. The paper is structured as follows: Section II describes the work related to our topic; Section III presents the characteristics of image classification in remote sensing; Section IV describes satellite images classification approaches and their advantages and disadvantages; Section V presents a comparative study of satellite image classification approaches; Section VI discusses the results of this study and finally, in Section VII, we conclude.

## 2. Related work

Satellite images are provided by different sensors and scanners operating in various electromagnetic spectrum bands [5]. They are two-dimensional, their intensity depending on the amount of average reflected or radiated energy associated with an area of the earth's surface or space in a wavelength band [6]. The electromagnetic spectrum is a combination of four types of wavelengths: visible light, infrared, microwave and ultraviolet.

Every object on earth has the power to reflect at different wavelengths. The radiation intensity is used to identify various objects on satellite data [6].

Image classification plays an important role in image analysis, remote sensing, pattern detection, and recognition. Sometimes the classification can be the object of analysis. For example, land use classification from remote sensing data produces a map image as the final product. Currently, there are different procedures for the classification of satellite images used for different purposes by various researchers [7].

Many scientific works aim to discover the methods and algorithms for classifying satellite images. There are two approaches for satellite image classification, and each has advantages and disadvantages: pixel-based classification (PBC) and object-oriented classification (OOC).

Many researchers have made scientific efforts in this field to compare and show the advantages and disadvantages of these two types of classification.

D. Jawak and al [4] have studied that the classifier for information extraction from satellite images is based on two types of learning: Supervised learning and unsupervised learning, and they have proposed several approaches to classification: Hybrid classification, Pixel-based classification (PBC) and Object-oriented classification (OOC). These authors consider that object-oriented classification overcomes the limitations of traditional methods based on the pixel approach because pixel-based classification is a traditional classification that does not work well on images that contain objects such as snow and ice, water, rock, and shadow.

Jabari and al [8] presented the main problems in high-resolution image classification, such as uncertainties in the position of object boundaries in satellite images and the complex similarity of segments with different classes.

Another supervised classification algorithm has been proposed by researchers Firozjaei and al [9]; this algorithm is called Homogeneity Distance Classification Algorithm (HDCA). It classifies satellite images using texture and spectrum information to classify these images in two additional iterative computational steps. These researchers also proposed an improvement to the Gravitational Search Algorithm (IGSA) to select features and determine the scale functionality of the space in HDCA [9].

Pelletier and al [10] proposed an extensive study on temporal convolutional neural networks (TempCNN) and recurrent neural networks (RNN). TempCNN is a deep learning approach applying convolutions in the temporal dimension to learn temporal and spectral features [3] automatically.

Several research works have tried to compare algorithms and methods for classifying satellite images [3,10, 11, 4, 12,13, 14, 15, 16, 17, 18].

Our work is also based on comparing these approaches and algorithms from the results of the implementations of previous works. Then according to a set of criteria, besides these two criteria: high spatial resolution, and segmentation, we have other criteria that we will discover in section V. What distinguishes our work from the other works mentioned above is that this work uses the Weighted Scoring Model (WSM)[19] which is one of the multi-criteria decision analysis methods. This method is adopted to make this comparison and get the job that is more favored for most criteria and discuss the result of this comparison.

## 3. Image classification in remote sensing

Remote sensing, particularly satellite imagery, is arousing great interest among the computer science community, which seeks to give machines the ability to recognize their environment through the classification of satellite images [20].

Satellite imagery is important for many applications, including territory monitoring, urban planning, disaster response, etc. [7]. These applications require an analysis of satellite images and, in particular, processing of the study area to detect and classify objects to solve the problems and challenges of this area. To apply this processing and this type of analysis, we must take into the type and resolution of satellite images (datasets), the type of satellite sensor, etc. Then we must choose the approach and the algorithm of classification.

Different approaches contain traditional, deep learning algorithms, each with advantages and disadvantages. In this section, we will mention the types and resolutions of satellite images and the different types of sensors. Then we will study each approach with its strengths and weaknesses.

### *3.1. Background*

*3.1.1. Resolution of satellite images*

Spectral resolution: It describes the ability of a sensor to use small windows of wavelengths. Many remote sensing instruments can record received energy at wavelength intervals (spectral bands) at different resolutions. It corresponds to the width, sensitivity, and location of the spectral bands and their number. The higher the spectral resolution, the higher the discrimination capability [3].

Spatial resolution: The smallest area covered by a single sensor at any time. The higher the spatial resolution, the smaller the pixels and, therefore, the greater the ability to distinguish the smallest details of the scene. A system with a spatial resolution greater than 1 km is considered low-resolution. The system with a spatial resolution of 100 m to 1 km is considered a medium resolution system. The satellite system with a spatial resolution of about 5 to 100 m is called a high-resolution system [3].

Temporal resolution is the time interval between image acquisitions or observations of the same scene such as revisit time and repetition rate. It depends on the viewing angle and the satellite orbit [3].

Radiometric resolution: The radiometric resolution of a remote sensing system describes its ability to recognize small differences in electromagnetic energy. The finer the radiometric resolution of a sensor, the more sensitive the sensor is to small differences in the intensity of the received energy. It refers to the number of gray levels of "digital number accuracy" used to display the data from scanners and sensors in the form of an image [3].

*3.1.2. Types of Satellite images*

Satellite images are generated by various sensors and scanners that operate in a variety of bands of the electromagnetic energy spectrum. There are 3 types of satellite images [6]:

Panchromatic images are images obtained in a wide band covering the entire range; only black and white images can be obtained. They are less rich from the point of view of spectral resolution, but they offer a higher spatial resolution.

Multispectral Images: They are a set of images acquired by several sensors that operate at narrow wavelengths and can be obtained in colour.

Hyperspectral images are obtained by sensors capable of recording information in a multitude, often more than 200 spectral bands much narrower than the multispectral images. Hyper-spectral data, therefore, provide more detailed information about the spectral properties of a scene.

Figure 4 shows a panchromatic image and a multispectral/hyperspectral image.

*3.1.3. Types of satellite image sensors*

Image capture by sensors can be done in either active or passive mode, which is illustrated in Figure 1.

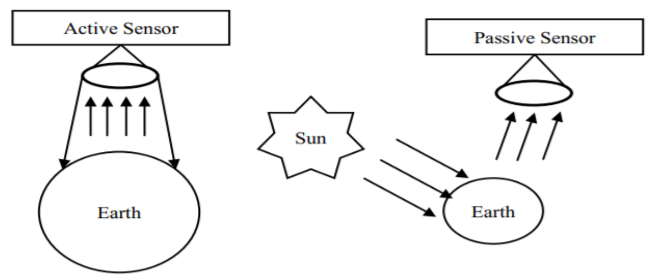



**Fig. 1 Active mode vs Passive mode** [6]**.**

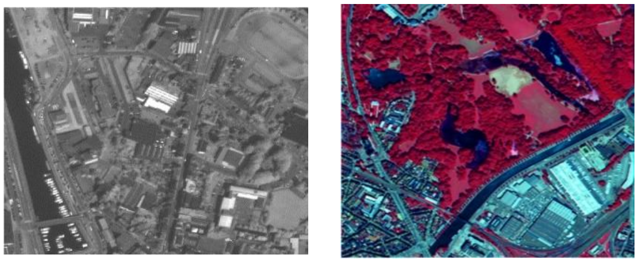
Satellite sensors are mainly divided into two types: Optical sensors and microwave sensors.

Optical sensors: There are visible and infrared optical sensors, each with different functionalities.

Visible optical sensors collect the strength of visible light rays that are reflected from the earth and objects and from which the user can understand the nature of the object, such as a river, mountain, sea, forests, etc. But the disadvantage of this type, they work poorly in the dark and in bad atmospheric conditions [6].

For infrared optical sensors, they collect infrared rays radiated by terrestrial objects. These sensors also capture high-temperature bodies on the earth's surface, even in the dark.

Microwave sensors collect microwaves reflected from the earth, objects independent of atmospheric conditions. Microwave sensors observe valleys, mountains, seas, rivers, and ice conditions such as thickness and temperatures [6].



(a) (b)

**Fig. 2 (a) Panchromatic image, (b) multispectral or hyperspectral image**

### *3.2. Types of classification*

*3.2.1. Unsupervised classification*

It is based on grouping pixels into several spectral classes. The spectral classes are manually labelled into the classes of interest [21]. ISODATA (Iterative Self Organizing Data Analysis Technique) classification is the most used method in remote sensing. It is an unsupervised learning method for satellite image classification. It creates a predefined number of unlabelled clusters in an image and requires several parameters that control the number of clusters and iterations to be performed. ISODATA uses the cluster-busting technique to label complex classes [22].

*3.2.2. Supervised classification*

It is based on selecting representative pixels for each of the desired classes and then executing one classification algorithm that labels the pixels of an image as information classes. Maximum likelihood classification is the most common supervised method in the literature [21]. Generally, ISODATA and Maximum Likelihood Classification methods are the most common methods applied for the pixel-based classification approach.

*3.2.3. Neural networks classification*

It is very powerful when used in a hybrid system with many types of neural networks [23, 24]. Researchers often use statistical modeling and machine and deep learning algorithms, including convolutional neural networks (CNN), recurrent neural networks (RNN), and generative adversarial networks (GAN). These methods offer new strategies for addressing complex geospatial data analysis tasks [25][11]. The capacity to learn sophisticated hierarchical features from multiple data sources allows deep learning methods to extract meaningful spatial and temporal patterns and infer information about the physical domain of urban areas and more abstract variables related to their inhabitants' socioeconomic conditions and quality of life [26]. This approach is more suitable for remote sensing image classification, especially hyperspectral and satellite image time series (STIS) [10]. The latter is an ordered set of images of the same scene acquired at different dates. This type of data provides rich information on the temporal evolution of the studied area. It combines high temporal, spectral, and spatial resolutions that closely follow the vegetation dynamics [10]. Generally, methods based on convolutional neural networks such as RNN, TempCNN, etc., have also been used to analyze and detect urban change.

## 4. Satellite image classification approaches and their advantages and disadvantages

Image classification is used to assign labels to an array of pixels that represent a single image. The classification procedure consists of three steps: the first step is the input of the training set data, for example, a set of N images, each labeled with one of the K different classes. Then, in the second training step, we use the input data to learn what each class is. We call this step model learning. Finally, in the last step, we evaluate the classifier's quality by asking it to predict the labels of a new set of images it has never seen before. Then we compare the real labels of these images to those predicted by the classifier [27]. There are two approaches to the classification of satellite images, each with its principle, characteristics, advantages, and disadvantages, as shown in Table 1 below.

### *4.1. Pixel-based classification (PBC)*

Pixel-based classification (PBC) is a traditional classification that uses the combined spectral responses of all pixels in a training set for a given class and is considered very effective for low to moderate spatial resolution data [3].

Pixel-based satellite image classification defines the class of each pixel in the image by comparing the n-dimensional data vector of each pixel with the prototype vector of each class. The data vectors usually consist of the gray level values of a pixel from multispectral channels. The training data is needed to train the classifier and is usually collected from aerial photos, geographic and satellite images, or a field survey [12]. Figure 4 shows the methodology of this approach, PBC.

Among the methods that are based on this type of classification, we have parallelepiped, minimum distance to the mean, and Maximum Likelihood Classification (MLC), the latter is the most widely used algorithm for classification based on pixels, and it has been shown to give the best results for the classification of remotely sensed natural resource data [12].

### *4.2. Object-oriented classification (OOC)*

Object-oriented classification is designed to deal with the problem of the environment's heterogeneity. It does not treat the pixel in isolation like the previous traditional approach; instead, it treats groups of pixels [3]. Instead of using pixels as the minimum unit, it divides the image into objects and uses the spectral, spatial, contextual and textual characteristics between them to classify them [3][4]. Table 1 shows the difference between the traditional PBC and this OOC approach. The basic process consists of two steps, namely segmentation and classification. Image segmentation is a preliminary step in object-oriented image classification that divides the image into homogeneous and contiguous objects [28]. Image segmentation techniques can be grouped into three types: thresholding/grouping, region, and edge [12][29][30]. Figure 4 shows the methodology of this approach to OOC.

Among the methods that are based on this type of classification, we have Random drill, K-means, SVM, and K-NN, these algorithms are the most widely used for object-oriented classification, and they have been shown to give the best results for the classification of resource data of geographic data [12].

## 5. Comparative study of satellite image classification approaches

A comparison of these two OOC and PBC approaches to satellite image classification is based on the WSM [22] method, which combines quantitative and qualitative measures to facilitate operational decision-making and allows each criterion to be assigned a weight according to its relative importance, with the most important criterion being assigned the highest weight.

There are five steps to applying the WSM [31]: The first step is to select the criteria, including costs and benefits, for evaluating each approach. The second step is to determine the weights of each criterion we will use to evaluate our approaches. The third step is to assign individual scores to each criterion, then calculate these overall scores to determine the ranking of the list of criteria. Finally, we will represent the results obtained using a spider graph. The goal of this graph is to show us the best approach to classify satellite images according to a set of scores for each criterion, such as the type of satellite resolution, texture, area, etc.

### *5.1. Criteria of comparative study*

PBC and OOC approaches contain many methods and techniques that can be used to classify satellite images. These methods and techniques include SVM, CNN, RNN, K-NN, RF, ISODATA, and K-means [3, 32]. It can be supervised or unsupervised or neural network type, and these classification methods can be pixel-based and object-based [3]. Each approach has its classification methodology, as shown in Figure 4.

**Table 1. Weakness and strength of satellite image classification approaches**

| Satellite image classification approaches | Weakness | Strength |
| --- | --- | --- |
| **Pixel-based classification (PBC)** [3][4][11] | • It is very effective for low spatial resolution data.<br>• The resulting signature includes the spectral responses of a group of different land coverages in the training samples, and the classification system simply ignores the impact of mixed pixels. | • It produces many unsatisfactory classification accuracy results with hyper-spectral data.<br>• It lacks visual interpretation.<br>• It is not ideal for HR and VHR satellite data.<br>• It cannot distinguish surface features from different objects with the same spectral characteristics.<br>• It automatically classifies all pixels in an image into thematic classes using only spectral information. |
| **Oriented-object classification (OOC)** [3][4][11] | • It results in higher accuracy, and it greatly improves classification accuracy.<br>• It can use the spectral information of the land types and the spatial position of the images, shape features, texture and context parameters.<br>• It is effective for high-resolution satellite images. | • Segmentation error: over-segmentation and under-segmentation.<br>• Over-segmentation is dividing a region into several segments, and under-segmentation is grouping several regions into one segment. |

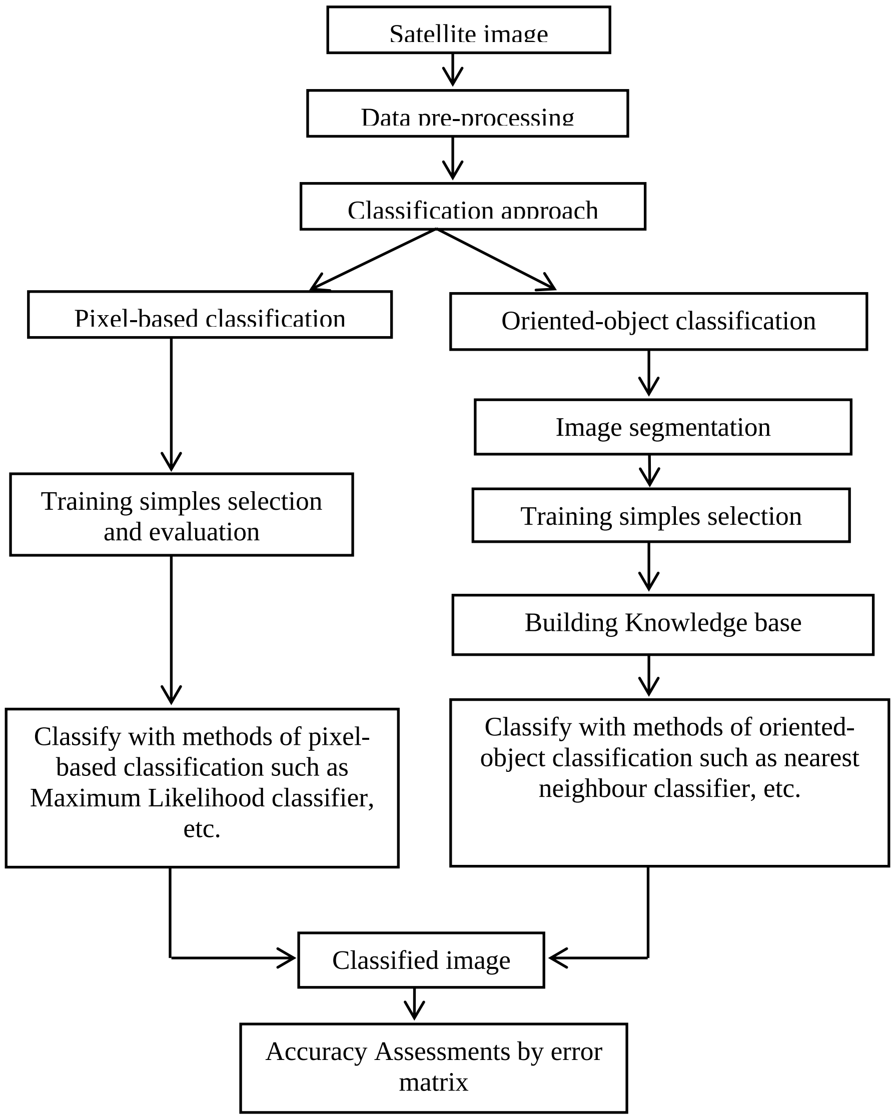



**Fig. 3 Classification technique flowchart: OOC vs PBC**[21]

The choice of criteria for comparing the PBC approach and the OOC approach is taken from previous works that have enriched the field of satellite image classification. We have identified seven criteria:

- High spatial resolution: This criterion depends on the quality of the input satellite image. It indicates the spatial resolution of the satellite image sensor. It shows the efficiency of the approach for classifying satellite images with a high spatial resolution. This criterion is evaluated in two values: 5, which means good, and 4, which means average.
- Segmentation: This criterion depends on the method of input image classification. It shows whether the segmentation phase is present in the classification procedure of each approach. This criterion is evaluated as a Boolean value that shows the availability of this criterion for each approach.
- Spectral/Color: This criterion describes the ability of a sensor to use small wavelength windows and corresponds to the width, sensitivity, and location of the spectral bands. It is possible to distinguish feature classes in a satellite image by comparing their different spectral signatures over a set of wavelengths. This criterion is evaluated as a Boolean value that shows the availability of this criterion for each approach.
- Shape/form: This criterion describes the shape information of the objects containing input images to classify them. This criterion is evaluated as a boolean value that shows the availability of this criterion for each approach.

- Area/Size: This criterion shows the information about the study area. This criterion is evaluated as a boolean value that shows the availability of this criterion for each approach.
- Texture: This criterion shows information about the texture of the study area. This criterion is evaluated as a boolean value that shows the availability of this criterion for each approach.
- Content: This criterion gives the contextual information of the study area. This criterion is evaluated as a boolean value that shows the availability of this criterion for each approach.

This information that each of these criteria gives us allows us to describe each class to give us a better classification. Table II shows the scores of each criterion corresponding to each approach based on the evaluation of each criterion we explained in this Section.

### *5.2. Application of Weighted Scoring Model*

Table III describes the WSM results for PBC and OOC satellite image classification approaches. The weighting percentages are assigned based on the importance of the criterion. Due to their mandatory nature, priority is given to the following criterion: high spatial resolution, a weight of 0.2 is assigned to this criterion. The second category of importance is given to the following criteria: Spectral/Color, Form/Shape, Area/size, Texture, and Content, a weight of 0.15 is assigned to these criteria. The last criterion, segmentation, does not have great importance. This criterion weights 0,05. The weight of the total scores is equal to 1.

**Table 2. Weakness and strength of satellite image classification approaches**

| **Criteria** | **Values of criteria corresponding to each model** | |
|---|---|---|
| | **Pixel-based classification (PBC)** | **Object-oriented classification (OOC)** |
| High spatial resolution | 4 | 5 |
| Segmentation | 0 | 1 |
| Spectral/ Color | 1 | 1 |
| Form/shape | 0 | 1 |
| Area/size | 0 | 1 |
| Texture | 0 | 1 |
| Content | 0 | 1 |

**Table 3. Weakness and strength of satellite image classification approaches**

| **Criteria** | **Weight** | **Requirement score** | |
|---|---|---|---|
| | | **Pixel-based classification** | **Object-oriented classification** |
| High spatial resolution | 0,2 | 0,8 | 1 |
| Segmentation | 0,05 | 0 | 0,05 |
| Spectral/ Color | 0,15 | 0,15 | 0,15 |
| Form/shape | 0,15 | 0 | 0,15 |
| Area/size | 0,15 | 0 | 0,15 |
| Texture | 0,15 | 0 | 0,15 |
| Content | 0,15 | 0 | 0,15 |

## 6. Results and Discussion

According to the previous results, the OOC approach is the most efficient for satellite image classification. It is an approach designed to deal with the problem of the environment's heterogeneity. It no longer treats the pixel in isolation as the other PBC approach; instead, it treats groups of pixels in their context. It improves classification accuracy because it uses all spectral, spatial, contextual, and textual information, contrary to the PBC approach, which uses only spectral information.

In terms of segmentation, this phase is mandatory in object-oriented classification. On the contrary, in the process of pixel-based classification, this phase is not included.

However, in terms of spatial resolution, the PBC approach is not the best approach for classifying satellite images with a high spatial resolution. Still, it presents a good classification result for medium or low spatial resolution satellite images.

Generally, methods and techniques based on object-oriented classification outperform pixel-based methods. This result is reflected in the multi-criteria radar graph presented in Fig. 4.

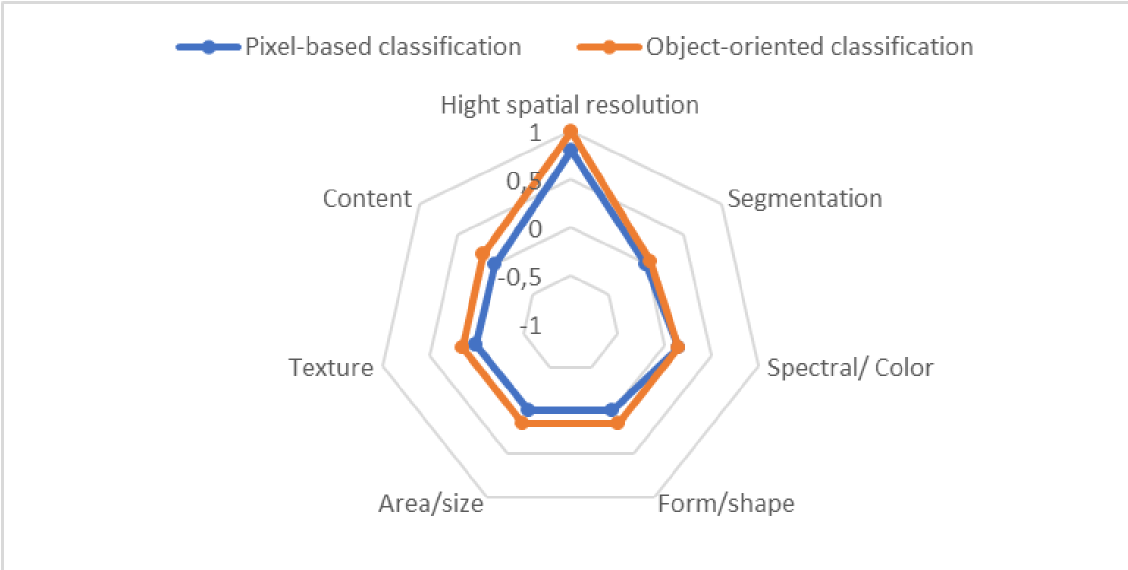



**Fig. 4 Spider Chart Multi-Criteria Decision**

Several works in the literature compare the OOC and PBC approaches. Still, they do not consider using multi-criteria decision analysis methods, which is a very important tool that can be applied to many complex decisions. For this reason, this article uses the WSM method, one of the multi-criteria analysis methods such as AHP, MAUT, etc., to address the lack of this type of comparison in the literature in the field of satellite image classification.

## 7. Conclusion and future work

This paper provides a comparative study based on the weighted scoring model. This study is a comparison between two satellite image classification approaches. This paper starts by identifying a set of relevant works that adopt the different methods and approaches of satellite image classification. Thus, we present the context of this study which contains the types and resolution of satellite images, the different types of sensors for these images, and then the different types of classification. Then, we described the two approaches to the classification of satellite images. We also saw the advantages and disadvantages of these approaches, and then we identified a set of criteria for each approach to make this comparison.

From this comparison study, we found two main approaches to the classification of satellite images: The classification based on pixels (PBC) and the classification-oriented objects (OOC). All image classification algorithms and methods can be either pixel-based or object-based. According to the result of our comparison, the most powerful approach is the object-oriented classification (OOC) because it uses all the spectral, spatial, textual, and contextual information to describe each class during classification processing and also performs the segmentation of the satellite image into groups of pixels, This means that this approach outperforms the pixel-based classification (PBC) approach because this approach treats each pixel, i.e. it does not use image segmentation and only uses spectral information.

Based on the weighted scoring model method, the scores of each of these approaches studied are obtained. These scores allowed us to establish a general ranking between these approaches, but they also showed their strengths and weaknesses concerning each studied criterion.

In future works, we will try to make implementations on the various algorithms and the various methods of classification of satellite images such as SVM, RF, CART, etc., which can be based on these two approaches, OOC and PBC, to make a comparative study between the metrics of each algorithm such as Accuracy, Kappa, Recall, etc. This work contributes to computer and data scientists to help them choose between the different existing approaches according to their needs and the criteria that matter most to them. This study aims to help the user choose the most efficient approach for his project.

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