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High-Resolution Satellite Image Processing for Dynamic Mapping in West Algeria

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DEDICATION

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ملخص :

يوضح هذا الوثيقة مشروع بحث متمحور حول تحليل صور الأقمار الصناعية عالية الدقة جدًا. يتناول التحديات التي تواجهها البيانات غير الكاملة، مثل الغموض والضوضاء والانحياز والاستكمال. الهدف الرئيسي هو تطوير أدوات منهجية لاستخراج وتوصيف الكائنات من هذه الصور، خاصة في المناطق الحضرية والحضرية النائية. تتكامل النهجات التي تعتمد على معالجة الصور ودمج البيانات والمنطق الضبابي لإدارة عدم اليقين بفعالية. يتكون الأطروحة من ثلاثة فصول تغطي بيان المشكلة، والتطبيق في البيئة الحضرية بما في ذلك المعالجة المسبقة ومعالجة البيانات، والخرائط الموضوعية لتصور وتمثيل المعلومات.

General Introduction

The problem concerns the nature of the information as an element of knowledge that can be encoded, stored, processed and communicated.

This information is often complex, coming from classifications or syntheses, and it comes in different heterogeneous formats from multiple sources with varying levels of reliability.

Whether by extraction or directly available, information is generally expressed through more elementary statements about its properties.

The information available may be imperfect in several ways:

- Ambiguous: when its purpose is not clearly defined.

- Noise: in the presence of random errors.

- Biased: subject to systematic errors.

- Incomplete: when essential elements are missing to characterize a situation.

- Imprecise: if it does not meet the expected precision standards, which can even be gradual (fuzzy) if the values are not clearly defined.

- Uncertain: when confidence in its veracity is partial.

- Incoherent (or conflicting): in case of contradiction with other information.

- Redundant: when available in several forms, although redundancy can sometimes clarify information.

Thus, we can schematically distinguish three main families of processing this information:

I) Development and interpretation to structure, merge, represent and explain it in order to communicate it effectively and draw new conclusions.

ii) The exploitation of information in decision-making, involving the search for optimal solutions, the evaluation of results according to various criteria, the proposal of decisions taking into account the uncertainty of the data and the evaluation of their reliability.

iii) Communication of information and consideration of the user's context, thus adding an important dimension to the way it is presented and interpreted.

Initial work objective:

The main objective of this VET is therefore to develop a series of methodological tools to analyze images at THRS and which best manage the difficulties mentioned above.

The chosen thematic application concerns the extraction and characterization of objects from THRS data acquired at different dates and from different sources in urban/ peri-urban environments.

These environments are very heterogeneous and subject to particular and irregular conditions in time and space; therefore, even if they are a real challenge for extraction, they appear particularly interesting to evaluate the developed methods.

We assume that the data is imperfect. To cope with these constraints, the methods developed in this PFE rely on an image processing approach based on data fusion and fuzzy logic.

This thesis seems to be logically organized and structured into four separate chapters, each dealing with specific aspects related to the analysis and exploitation of very high spatial resolution remote sensing (THRS) images. Here is a summary of the organization:

I.1 Introduction and Issues:

- This chapter presents the research problem.
- It offers a state of the art based on the analysis of the scientific literature.
- Evaluates data and methods to observe THRS image characteristics.
- It takes stock of the methods used to assess uncertainty.

I.2 Application of the Methods:

- This chapter applies methodological tools to THRS images.
- It focuses on extracting information in a specific urban/peri-urban context.
- It presents the radiometric and geometric pretreatment phases, as well as the processing to extract the information.

I.3 Mapping and Visualization:

- This chapter develops the cartographic part to enhance the information obtained.
- It offers new visualization and mapping tools.
- It presents examples of achievements, offering new perspectives in the field of thematic mapping.

This structure allows a logical progression of the understanding of the subject, starting from the problem to the presentation of results and future perspectives.

Here's a short summary of the provided text in English, followed by French and Arabic translations:

Chapiter1: multi-source data time refection

SOURCE DATA:

Multi-source data, such as data from remote sensing, maps and other sources, are crucial but complex.

They come in various forms, including matrix, vector and point, each with its advantages and disadvantages. However, object detection algorithms are struggling to adapt to this diversity of sources.

The advent of Very High Spatial Resolution has revolutionized the detection of objects, but has also posed challenges with the multiplication of sensors, resulting in image variability due to various parameters such as scan conditions and sensor characteristics.

Types of data:

The data used in remote sensing is divided into three distinct forms of representation: matrix data, point data and vector data.

These three types of data, resulting from modern technological advances, each have their advantages and disadvantages.

However, algorithms designed for object detection encounter difficulties in adapting to different data sources

traditional images.

There are several reasons :

.1 The technologies used vary and are presented in different data formats. Therefore, the representations, accuracy and structure of the data differ.

.2Data, or images, are saved at different resolutions and in different geographic reference systems

Characteristics of THRS data:

The introduction in the late 1990s of the Very High Spatial Resolution (THRS) has brought significant advantages in the detection of objects, but in parallel, it has complicated the application of traditional methods.

One of the current problems in the processing of remote sensing satellite data concerns the multiplication of sensors.

The images provided by this diversity of sensors show differences due to several parameters at the time of capture: the variability of the acquisition conditions, the sensitivity of the sensors, the atmospheric conditions, and the specific characteristics of each sensor

Table I-1: Characteristics of THRS sensors (Benjdia, 2008)

	Ikonos		Quick-bird-2		Spot5		Orb-view-3		Kompsat-2	
Compagnies	Space Imaging (USA)		Earth Watch(USA)		Spot image (Europe)		Orb image(USA)		Spot image (Korea)	
Date de lancement	9-1999		10-2001		5-2002		06-2003		28/07/2006	
Altitude(km)	681		450		822		470		685	
Bandes Spectrales	Pan	MS	Pan	MS	Pan	MS	Pan	MS	Pan	MS
Longueur d'onde(µm)	0.45-0.9	0.45-0.52 0.51-0.59 0.63-0.7 0.76-0.85	0.45-0.9	0.45-0.52 0.52-0.6 0.63-0.69 0.76-0.89	0.51-0.73	0.5-0.59 0.61-0.69 0.79-0.89 1.6-1.7	0.45-0.9	0.45-0.52 0.52-0.6 0.63-0.69 0.76-0.89	0.5-0.9	0.45-0.52 0.52-0.6 0.63-0.69 0.76-0.9
Résolution spatial(m)	1	4	0.6	2.4	5	10	1	4	1	4
Résolution radiométrique	11bits		11bits		8bits		11bits		-	
Répétitive	1.5-3jours		1-3.5jours		1-4 jours		3jours		-	
Orbite	héliosynchrone		héliosynchrone		Héliosynchrone		héliosynchrone		Héliosynchrone	
Angle devisée	+ou-22.5°		+ou-25°		+ou-20°		+ou-25°		-	
Stéréoscopie	Oui		Oui		Oui		Oui		Oui	
Taille delà scènekm²	11*11		16.5*16.5		60*60		8*8		15*15	

the table below shows the characteristics of the various very high spatial resolution (THRS) sensors.

The spatial resolution:

Remote sensing images consist of a grid of elements called pixels.

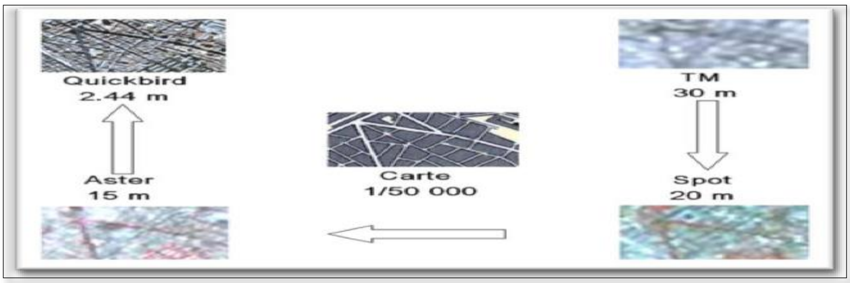
The pixel is the smallest unit of an image.

It is usually square in shape and represents part of the image.

However, it is crucial to differentiate between pixel spacing and spatial resolution.

The decrease is undoubtedly the element that has the most impact on the interpretation of THRS images. This impact concerns both the theoretical approach to interpretation and image quality. At the theoretical level, the arrival of THRS images radically changes the possibilities of interpretation. For the first time in the history of civil satellite remote sensing, image resolution is smaller than the size of major urban objects (buildings, trees, roads, etc.) (Man, 2005).

Figure I-1: Intersection of roads shown at different resolutions



than the size of major urban objects (buildings, trees, roads, etc.) (Man, 2005).

Spectral resolution:

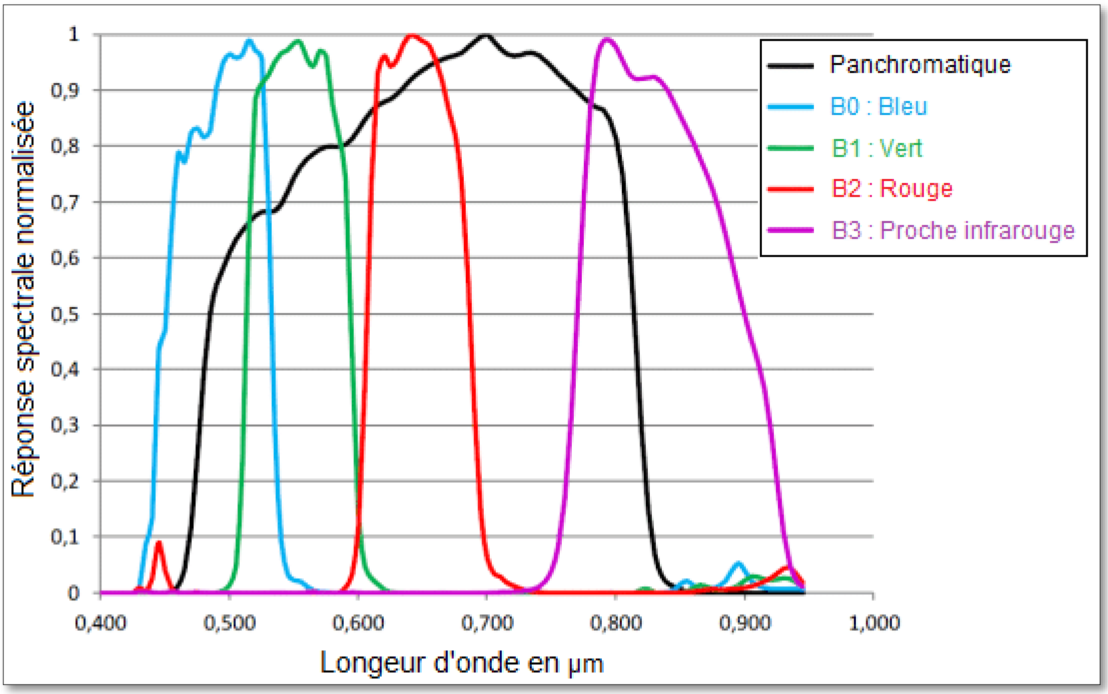


Figure I-3 presents a standardized spectral band response for Quick-bird (THOMAS 2006)

It is often possible to distinguish different classes of characteristics and details in an image by comparing their responses over different wavelengths.

Very large classes, such as water and vegetation, can be differentiated using a wide range of wavelengths (such as visible and infrared for example).

On the other hand, more specific classes such as different types of rocks are not as easy to differentiate and require the use of a much finer wavelength interval.

Currently operational THRS sensors are limited to visible and near-infrared spectral domains, and the number of bands is generally limited to 4 (with the exception of a medium infrared band for the Spot 5 sensor).

The Orb-view 4 satellite, for which a hyper spectral sensor of 200 bands was planned (with a spatial resolution of 5 meters), would have brought another dimension to this type of images.

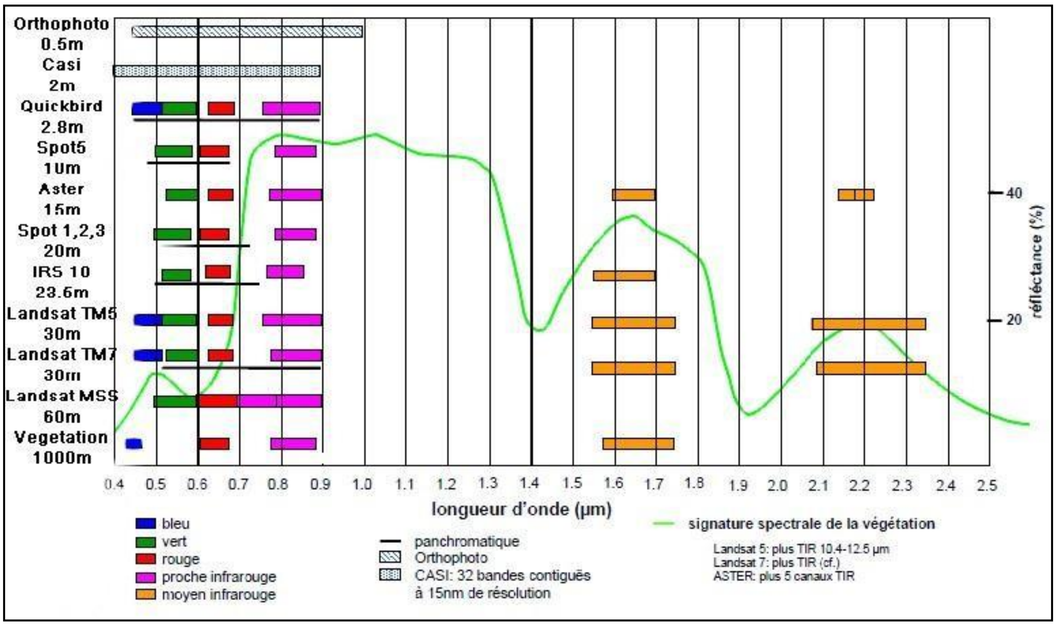


Figure I-4: Spectral band interests (Bousaid 2007).

Radiométriquerésolution.

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 it is to small variations in the intensity of the energy received.

The radiometric resolution is usually 11 bits (with the exception of Spot 5, which remains at 8 bits).

It reflects the ability to render on the image the fineness of the measurements. In this sense, THRS sensors seem better adapted to the discrimination of certain materials.

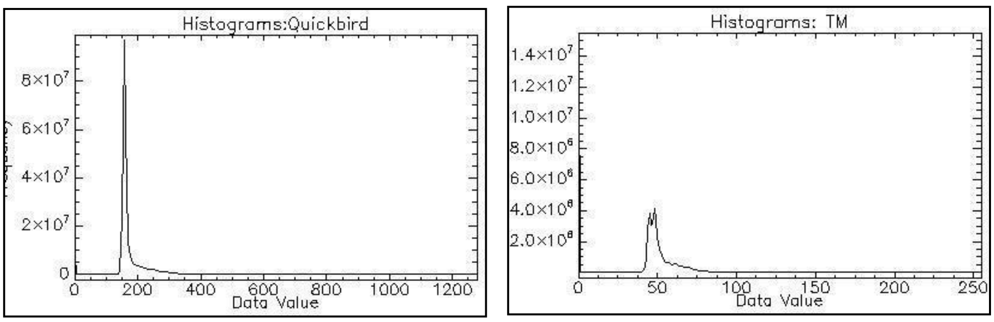


Figure I-5 : Histogrammes des images Quickbird et TM.

Temporal resolution:

In addition to spatial, spectral and radiometric resolution, another important concept in remote sensing is that of temporal resolution.

This is the time between successive passages to the nadir of a satellite, that is, the time required for a satellite to perform a complete orbital cycle.

This period is usually a few days for most THRS sensors.

Some satellites also have the possibility to point their sensors towards the same point for different passages of the satellite (Canadian Centre for Remote Sensing).

Visibility of building facades:

New information is therefore available, which allows a change in the scale of interpretation.

With THRS images, we move from the interpretation of land use classes to the identification of objects.

This change of course influences the choice of interpretation methods.

The decrease in spatial resolution first increases the impact of geometric disturbances on image quality, especially through geometric errors related to the presence of high objects.

In extreme cases, these errors can lead to misinterpretations (appearance of building facades for oblique-aimed images) (men , 2005).

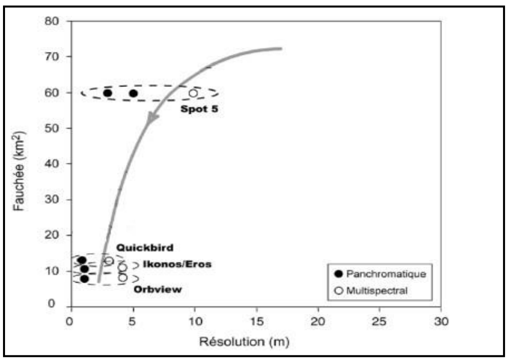


Figure I-7: Relationship between mown and spatial resolution «Modified from Mighty, 2003».

The decrease in spatial resolution ultimately results in an increase in the amount of data. Comparing a Quickbird image and a TM image for the same floor area, the Quickbird image has approximately 268 times more pixels for the panchromatic band and 69 times more pixels for a multi-spectral band.

For the same surface, storage requirements and treatment duration are therefore increased (Lhomme, 2005).

The question of mixing

A mixel is a pixel whose surface area is occupied by several types of land use. It shows a “mixed” spectral signature that is the sum of contributions from land use types (Lhomme, 2005).

Until the late 1990s, one of the main problems associated with remote sensing images was that a pixel could represent an area composed of several objects of very different natures (especially since spatial resolution is low).

This is called mixed pixel or mixel.

In fact, low-resolution images only allowed an analysis of thematic areas (dense or sparse built-up area, vegetation, water, etc.) and/or structural landscape (extraction of road or rail networks for example) (Kurtz, 2009).

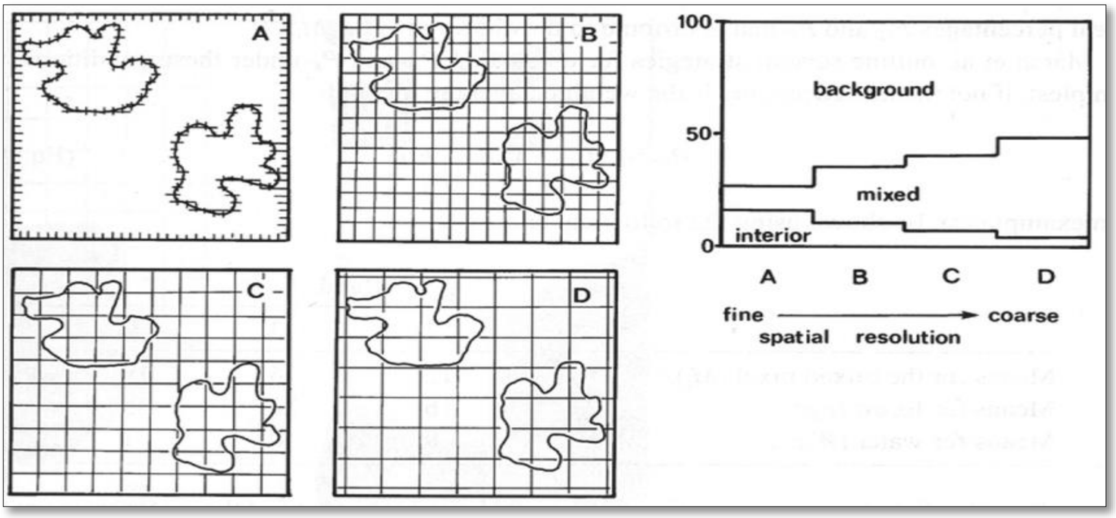


Figure I-8: Effects of spatial resolution on the proportion of mixels (Lhomme, 2005).

Object detection potential on THRS images:

By passing "below the threshold" of the size of urban objects, the spatial resolution of THRS images forces to rethink both the theoretical and methodological approach to the interpretation of images.

Classical methods of interpretation based on spectral signature analysis aim to discriminate these same classes.

They presuppose a unique signature for each of the classes of interest, and their performances are therefore related to the relationship between spectral classes and land use classes. In the case of the identification of urban objects from THRS images, this relationship is restricted by two interrelated elements: the theoretical change in the type of interpretation and the impact of resolution on image quality (Lhomme, 2005).In the field of scene analysis, there are many terms to describe or qualify land cover or land cover.

Many of these terms correspond to objects whose visibility depends on the resolution of the image. Thus, there is a wide range of classifications of objects associated with satellite images such as the Corine Land Cover nomenclature defined for Landsat images at 30 m, the Spot nomenclature defined for Spot images from 5 m to 20 m, or the BDCartocIGN database for aerial photos and 2.5 m spot images.

For example, the Corine Land Cover nomenclature makes it possible to characterize land use patterns on a scale ranging from 1/100,000 to 1/50,000 (Table I-2). This nomenclature proposes three levels of semantics.

Note that a fourth level is often added for a 1/25,000th analysis allowing, for example, to specify the density of built-up areas (table I-3, left column).

Table I-2: Extract from the Corine Land Cover nomenclature used for mapping urban areas

1:1 000 000 -Level1	1:100000 -Level2	1:50000 -Level3
1.Artificialsurfaces	1.1. Urban 1.2. Industrial,commercialandtransportunits 1.3. Mine,dumpandconstructionsites 1.4. Artificial,nonagriculturalvegetatedareas	1.1.1. Continuousurban 1.1.2. Discontinuousurban 1.2.1. Industrialorcommercialunit 1.2.2. Roadandrail networks 1.2.3. Portareas 1.2.4. Airports 1.3.1. Mineralextractionsites 1.4.1. Greenurbanareas 1.4.2. Portandleisurefacilities
2.Agriculturalareas		
3. Forestandsemi-natural 4. areas		
5.Wetlands		
6. Waterbodies	6.1. Inlandwaters 6.2. Marinewaters...	6.1.1. Watercourses 6.1.2. Waterbodies

Table I-3: Extract from nomenclature for analysis of HR and THR images. (Wemmert, 2009)

1 :25 000 Level4:Arealevel	1 :10 000 Level5: Blocklevel	1 :5 000 Level6:Urbanobjectlevel
• High-densité urbain fabrique • Low-densitéurbain fabrique • Industrialiseras • Forest zones • Agricultural zones • Water surfaces • Brazil	• Continuos urban blocks • Discontinuous urban block individual urban blocks Collective urban blocks • Industriel urban blocks • Urba végétation • Forest • Agricultural zones • Water surfaces • Road	• Building/roofs : Light gray residential roof,orange tile roof, . . . • Vegetation :green vegetation , non-photo synthetic vegetation,... • Transportation :Streets, parking lots, • Water surfaces :river, ,. • Brazil • Shadow

While the low resolution images (HR images) only allowed an analysis of thematic areas (Table I-3, level 4), the images with metric or su metric resolution allow an analysis of the geographical objects themselves: house, tree, etc., via their materials, corresponding to a 1/5,000th analysis (Table I-3, level 6).

However, it should be noted that the increase in pixel fineness can significantly disrupt the analysis.

New objects appear in the images without being always necessary for analysis.

The most notable example is that of vehicles on roads and in car parks. It is obvious that, outside the context of traffic analysis, the notion of road (or parking) is independent of the color, number and position of vehicles on it at a given time.Network extraction is complicated and may require a preprocessing step to smooth the image to remove small objects.The figure (Figure I-9) shows a bus station and vehicles in use.

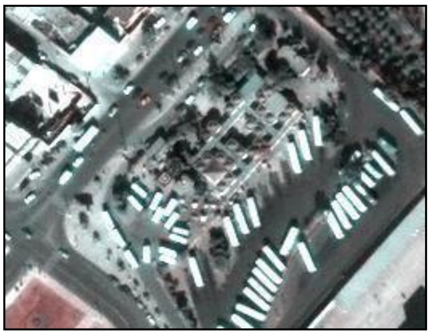


Figure I-9: The appearance of small objects - Extract from an image

Moreover, in the field of urban analysis, more and more users need to analyze images in terms of urban blocks (or blocks).

An urban block is often defined as an urban area delimited by a minimum cycle of communication networks (Figure I-10).

This level of analysis is effectively a 1/10,000 scale analysis (Table I-3, Level 5). However, in this case, no spatial resolution allows them to be extracted directly. Indeed, HR images have a too coarse resolution while THR images need to rebuild the islands.

There is therefore an intermediate semantic level in the levels of analysis that does not correspond directly to an image resolution interval.

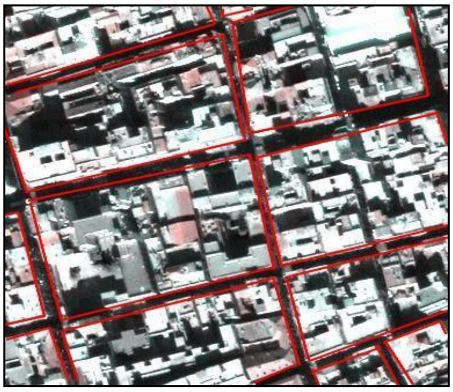


Figure I-10: Blocks: houses bordered by roads.

1. *Geometric quality of THR images*

For THR images, the geometric distortions caused by the relief are actually more annoying, since the ratio between the relief variations and the pixel size increases considerably.

Thus, the geometrical position of the buildings is disturbed by the variations of terrain on the whole image, but also by the local variations due to the reliefs generated by the buildings themselves.

Many studies have been carried out on the geometric quality of THR images, and more specifically on those of Ikonos images.

Examples include: (Baltsavias , 2001), (Ganas, 2002), (Jacobsen, 2002), (Dial, 2003) and (Toutin, 2003).

The positioning accuracy of the basic products "Geo images" provided by the image distributor "Space-imaging" is 50 m with a 90% confidence rate (Toutin, 2003).

In extreme configurations such as steep mountains, errors can be greater.

Thematic errors can then be added to geometric errors. If the relief shows strong variations, some areas such as valley bottoms may not appear on the image.

Correction methods, using digital field models, have been developed specifically for THR images.

Their performance depends in part on the accuracy of the numerical models used (Lhomme, 2005).

I.4 Semantic Quality:

The decrease in spatial resolution also amplifies the impact of signal disturbances on image quality.

These disturbances are due in particular to the topography of urban environments and the heterogeneity of materials.

The direct consequences for interpretation are the decrease in the thematic significance of spectral signatures, the increase in local variance and the appearance of shadow zones (Lhomme, 2005).

In order to estimate the importance of these problems, we will first analyze the impact of the shadow, then more generally, the confusion of spectral signatures (Lhomme, 2005).

I.5 The shadow

The shadow on an image is generated by the absence of direct illumination due to the presence of reliefs between the shaded area and the solar radiation.

In order to estimate the area occupied by the shade, we carried out an extraction of the shade by simple threshing of the gray levels (the water zones were previously masked).

a) Raw image with shadow.

b) Shadow image only.

Figure I.11: Shadow images "Quick-bird Oran

The shadow thus extracted occupies about 14% of the total image, percentage of the shadow compared to the other themes (Water, vegetation, Urban, Bare soil).

The most shaded areas are in urban areas and on the edge of wooded areas. Within the urban environment, there are differences depending on the size and density of the buildings.

In order to estimate these differences, we selected five representative extracts of different urban tissue types from the image.

We then estimated, for each of them, the areas occupied by the shadow.

Results ranged from 19.18% for a small-block area to 36.26% for a downtown area, 17.06% for buildings on the edge of the city, 10.19% for relatively flat land, and 41.62% for areas with rough terrain.

These estimates should be considered with caution; they are only indicative. The method of extracting the shadow used (gray level thresholding) is very simple.

It does not distinguish between different types of shadows (litter, projected and penumbra) or very dark surfaces (tarred roofs) that can be confused with shade, as shown in the example in Figure I-13.)

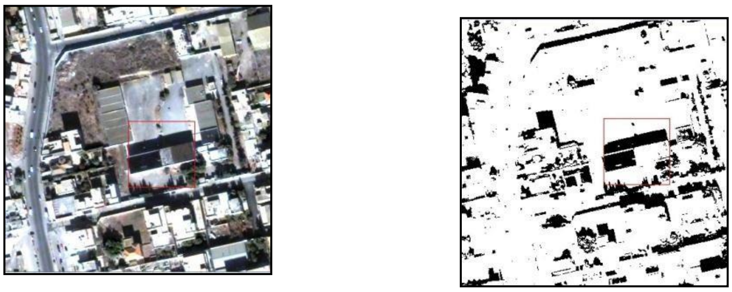


Image shadow

Figure I-13: Shadows of Tarmac Roofs

2. Spectral Confusions

There are different types of confusions that can, to varying degrees, decrease the performance of object extraction methods. If we consider the objects individually, different spectral signatures can correspond to the same object.

If we consider all the objects, we find different spectral signatures for the same type of object, but also identical spectral signatures for different types of objects.

These confusions are logically present on the image of Quickbird.

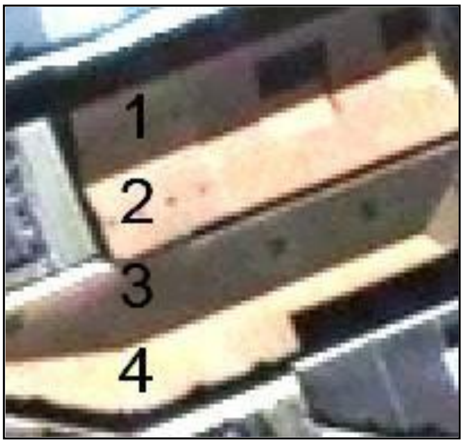
We illustrate each of the types through examples.

3. Effects of differences in illumination

Differences in spectral signatures within the same object may be due to differences in orientations causing deviations in the illumination and reflection of objects, the most pronounced consequence of which is the presence of shadow.

This phenomenon is illustrated on an image extract (figure below representing a construction), from which we noted the spectral values (the values of the curves corresponding to the average value of the measurements made on 3 pixels for five significant points of the different orientations).

We observe that the appearance of spectral signatures is generally similar, but that there are significant differences between the values. The analysis of the pixels composing the whole object confirms these results, since we observe a spread of gray levels ranging from 0 to 255 for the 4 bands (Lhomme, 2005).



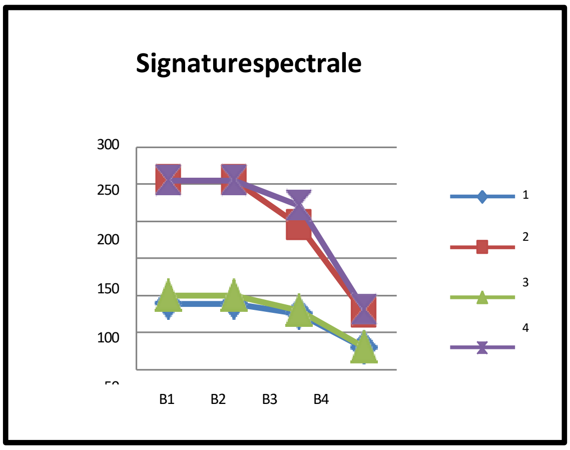
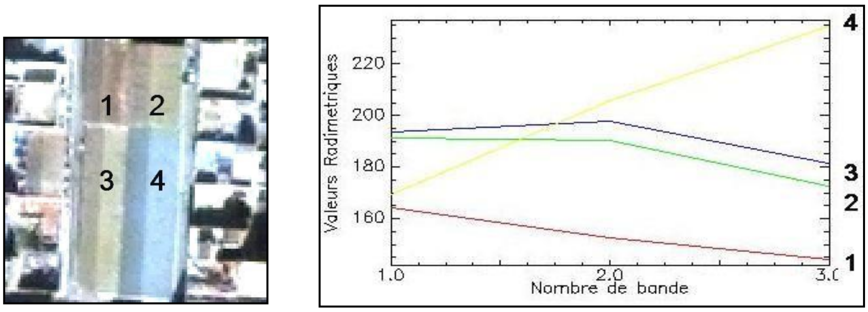
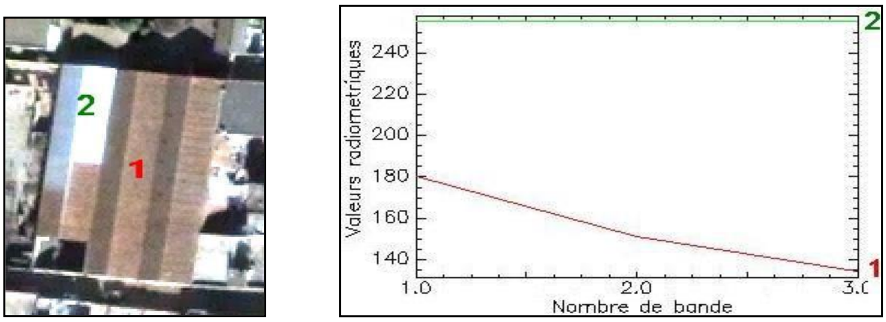


Figure I-14: Different spectral signatures for the same object.

These differences can also be caused by the presence of different materials in the composition of the same object. This is illustrated by the two examples below:



-A-



-B-

Effects of different materials

Spectral confusions are also present within the same object class.

They are mainly due to the use of different materials in the construction of objects

We illustrate this in Figure I-16 which shows differences in the spectral signatures of different buildings extracted from the Quickbird study support image (the values of the curves corresponding to the average value of the measurements taken throughout the building).

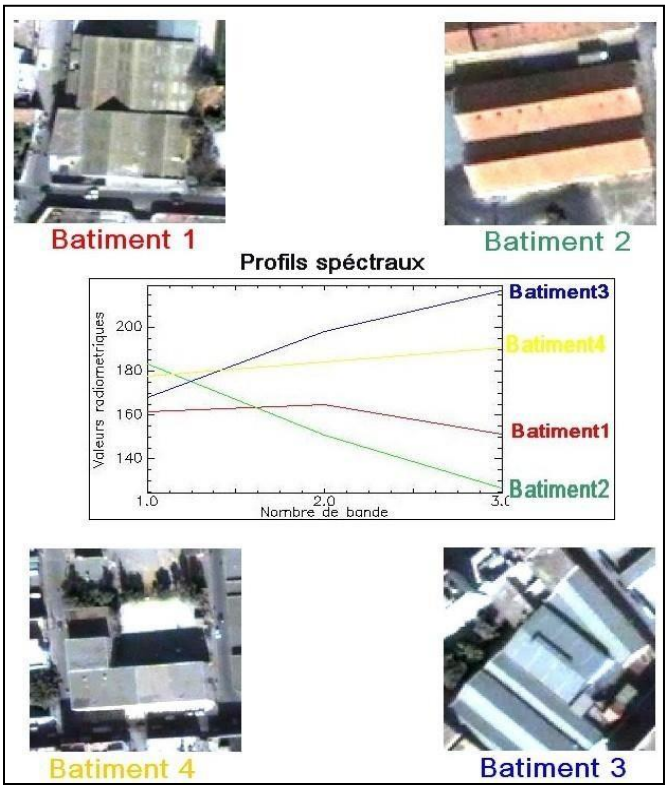


Figure I-16: Different spectral signatures for the same type of object (buildings)

4. *Similarities in spectral signatures for different types of objects*

The spectral detection of urban objects is further complicated by a last type of confusion.
These are the similarities that can exist between the spectral signatures of pixels belonging to different types of objects.

Figures I-17 and I-18 show two examples of similarities in spectral signatures (using the ROI function, Envi software) between buildings and roads, and buildings and yards.

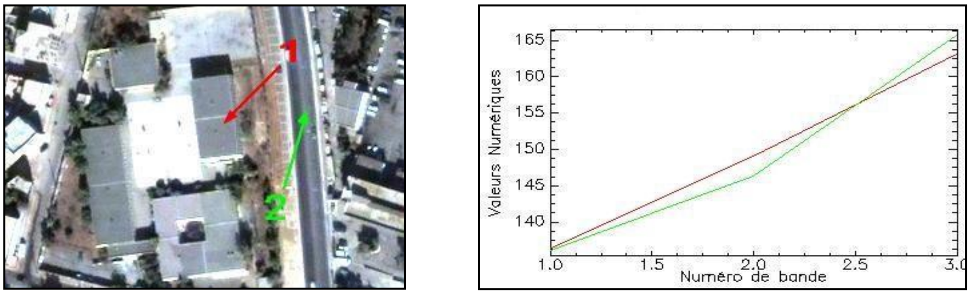


Figure I-17: Confusion of signatures for different object buildings and roads

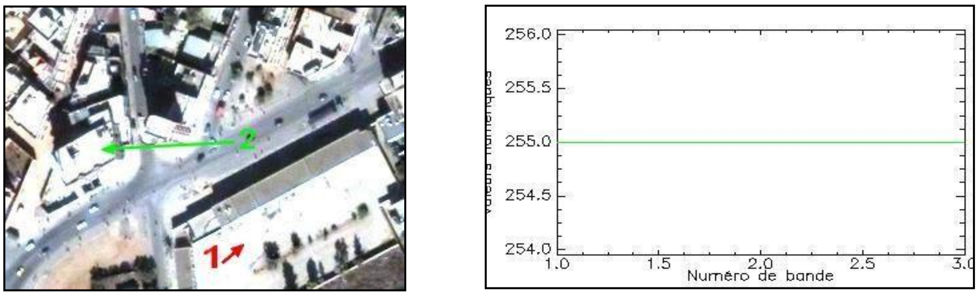


Figure I-18: Confusion of signatures for different objects

«buildings & courtyard»

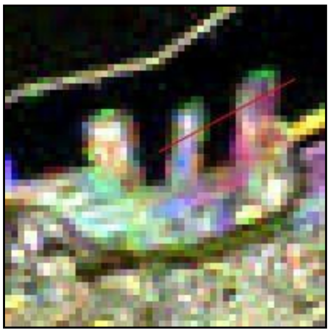
5. *Change in radiometric values of the same object:*

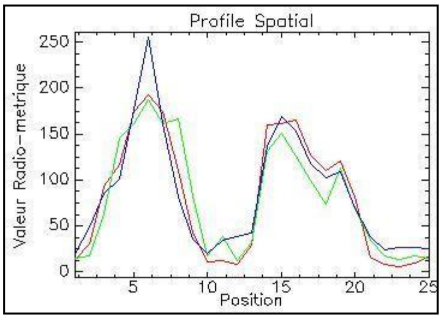
Another source of error on satellite images is the change of radiometric values in different illumination conditions even if the object has not changed shape or size, which causes confusion between the objects.

Figure I-19 shows extracts of the blue band of the TM images (30 meters) combined at different dates in 2006, 2009 and 2011 (Oran port area).

Figure 23_b shows two sections of a line located in the center of the image, marked by a red arrow.

The B2006, B2009 and B2011 modalities correspond to the solid line and dashed curves respectively.





a)B_2006+B_2009+B_2011. **b) Graph of radiometric values.**
(2011 - 2009 - 2006)

Figure I-19: TM blue band spectral signature for 2006, 2009 and 2011

Although THR images now allow to extract a very specific semantics (at the level of the urban object, corresponding to level 6 of table I-3),

it is very difficult to extract a more general semantics (urban area) immediately.

The old generations of images (HR, BR) are therefore always of particular interest for the extraction of this kind of elements.

Moreover, depending on the type of analysis carried out on urban environments, users' needs in terms of image resolutions are different (Kurtz, 2009).

Nevertheless, the multiplication of the number of THR acquisitions as well as their availability to a wider public often make it possible to obtain, for the same captured scene, several distinct descriptions of it.

According to the analyzed resolution, the information that can be extracted is different but complementary and hierarchical (buildings vs. residential areas).

This complementarity of information is becoming more and more frequent, and a solution to make the most of it is no longer to analyze the images independently but to take into account all the resolutions made available by the expert during this analysis phase (Kurtz, 2009).

6. *IMPERFECTIONS IN INFORMATION*

The sources of information are of different kinds. This information is generally imprecise, uncertain and incomplete. In view of this imperfect information, we have three options:

(a) we seek to remove them

b) either we tolerate them and then we must ensure that the algorithms involved are robust in the face of these imperfections

c) or we try to model them. The imperfection of information involves several concepts. The first concerns the vagueness of information.

It is usually mastered. The second concept concerns uncertainty, to be distinguished from imprecision by the fact that it does not refer to the content of the information but to its quality.

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It is usually mastered. The second concept concerns uncertainty, to be distinguished from imprecision by the fact that it does not refer to the content of the information but to its quality.

The information is also redundant and complementary.

8. *Redundancy*

Redundancy of information or sources is having the same information several times.

Fusion relies on the redundancy of sources to confirm information.

For example, the observation of the same object by different sources can make it possible to locate it accurately and to represent it in a space of higher dimension.

The redundancy of information from one source with another can be defined from a measure H of the amount of information provided by one source. Thus, the information redundancy of an S1 source with a S2 source can be written:

R(S1,S2)=H(S1)+H(S2)-H(S1,S2) **(EquationI.1)**

where H(S1 , S2) refers to the amount of information provided by both S1 and S2 sources.

However, this definition cannot be extended without losing the positivity of redundancy.

However, we can calculate the redundancy of one or more sources with one or more other sources by considering the amount of information from these sources (Martin, Information Fusion, 2005).

$$R((S,\dots S_j),(S_{j+1},.S_m))=H(S_1,\dots S_j)+H(S_{j+1},...S_m)-H((S_1,\dots S_j),(S_{j+1},...S_m))$$

(EquationI.2)

9. *Complementarity*

Sources or information are complementary if they are of a different nature and make it possible to specify the response of the system.

The complementarity of information from one source with another can be measured by measuring the amount of information from one source, for example:

C(S1|S2)=H(S1|S2)=H(S1,S2)-H(S2) **(EquationI.3)**

This definition makes it possible to logically write that the amount of information of a source is the sum of the redundancy of the information of that source with a second source and the complementarity of the information of that source with respect to the second:

H(S1)=R(S1,S2)+C(S1|S2) (EquationI.3)

This definition of the measure of information complementarity can be written for one or more sources in the same way as equation (2) (Martin, Information Fusion, 2005).

10. *Vagueness*

Inaccuracies correspond to a difficulty in the statement of knowledge, either because numerical knowledge is poorly understood, or because natural language terms are used to vaguely describe certain features of the system .

The first case is the consequence of insufficient observation instruments, measurement errors, etc.

The second comes from the linguistic expression of knowledge or the use of classes with poorly defined limits (vegetation, soil, urban, etc.) (Martin, 2005.(

11. *Uncertainty*

Uncertainties, meanwhile, concern a doubt on the validity of a knowledge. They can come from the reliability of the observation made by a system.

It can be safe, capable of making errors or intentionally giving erroneous information, or face a difficulty in obtaining or verifying knowledge

They also characterize the degree of compliance with the reality of an information, or the assurance of a source in the information provided .

Uncertain information therefore describes a partial knowledge of reality, whereas what is certain necessarily entails knowledge of all reality .

To measure uncertainty, reality must therefore be known as a land use map (Martin, 2005).

12. Links between uncertainty and imprecision

The vagueness of information is often mistakenly confused with uncertainty.

Imprecision is therefore a quantitative defect of knowledge, while uncertainty is a qualitative defect of knowledge.

In addition, the main cause of the uncertainty of an information comes from the imprecision of the information.

Indeed, in the case of quantitative information, the imprecision of a data leads to uncertainty on the information conveyed.

Similarly, uncertainty can lead to imprecision.

For example, saying that the pixel is 10 when it is 20, causes uncertainty about the radiometric value it makes. Similarly, doubt about the assignment of an object such as “vegetation” can lead to imprecision about the estimate of the number of pixels that are of vegetation type.

These two imperfections are often present simultaneously (Martin, 2005).

13. Other imperfections

There are other kinds of imperfections, more or less dependent on imprecision and uncertainty, such as incompleteness, conflict and ambiguity

14. Incomplete

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Similarly, doubt about the assignment of an object such as “vegetation” can lead to imprecision on the estimate of the number of pixels that are of vegetation type.

These two imperfections are often present simultaneously (Martin, 2005).

• Either it is a lack of information (for example, a feature does not provide information when it is supposed to, as in the case of a transmission failure)

• Either, the incompleteness is due to a lack of modeling of the source or problem (for example, a radar does not provide an image of submerged submarines, information relating only to the surface of the water).

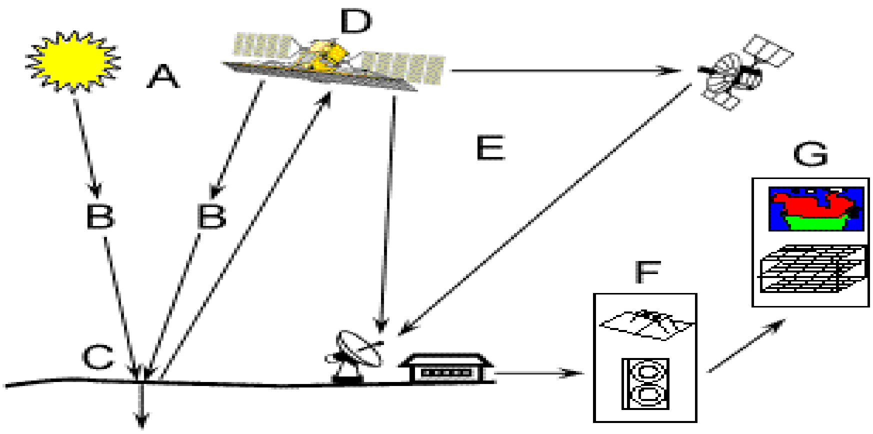


Figure I-21: Data acquisition scheme in remote sensing

In Figure I-21, we show that we can never acquire the target "C" as it is in reality in part "G".

15. Conflict:

Two or more pieces of information conflict if they are contradictory. The conflict can also be reported to the source by extension.

A measure of conflict between information from several sources is defined, it can be called merger inconsistency.

The inconsistency represents both the conflict (for example a sonar source detects a mine at a location, while the sounder describes a rocky material).

The inconsistency (the conflict leads to an inconsistency in the conclusion existence of a mine in rock matter), the temporal inconsistency (for example a radar detects an oil slick on the water surface at 16h, while another radar

describes the area without pollution at 16:15) and the confusion which is a lower inconsistency (for example a radar announces the arrival of an aircraft at 16:15, while it arrives at 16:00) (Martin, 2005).

- The origins of the conflict stem essentially from three situations:

- Sources are unreliable. Information is inaccurate and can lead to ambiguity. The framework for discernment is non-exhaustive.

The hypothesis of a closed world is then false.

- The sources observe different phenomena. In this case the information should not be combined.

In addition to the defects, other elements of the data are analyzed, such as the temporal nesting of the data or the geographical characteristics of the data required for image processing.

16. Ambiguity

The ambiguity of information is the fact that it involves two or more interpretations.

Ambiguity can come from another imperfection of information (Uncertainty, imprecision, conflict, ...), but not necessarily.

For example, the description of a radar target (by its signature) does not always distinguish this target from another, when the signatures are too close, it is the case of an imprecise signature.

Merging information from another source can help to remove this ambiguity.

We have seen that measurements of information imperfections can be done by measuring the amount of information.

Shannon entropy is often used for this measurement.

The entropy of a source, or the contribution of information from a source for a signal x is defined by:

$H(Sj(x)) = -p(Sj(x)) * \ln(p(Sj(x)) = - nMj(x) * \ln(Mj(x)))$ (Equation I.5)

The entropy of a set of sources is then given by:

$H(Sj(x)….Sm(x)) = -p(Sj(x)…..Sm(x)) \ln(p(Sj(x)…...Sm(x)))$ (Equation I.6)

In addition to the defects, other elements of the data are analyzed, such as the temporal nesting of the data or the geographical characteristics of the data required for image processing.

17. QUALITY OF DATA

18. Data quality in geographic information

Several standardization committees have dealt with the definition of spatial quality.

The objective was to put in place quality criteria as well as measures to evaluate these criteria.

In the past, the quality of spatial data was limited to the accuracy and precision of information.

Then, the notion of nominal terrain was introduced to clarify the notion of accuracy.

The fundamental concept of “nominal terrain” emphasizes that the accuracy of a test cannot be performed naively.

The test does not take place in a "real" world, but rather in a "nominal" world where objects are classified according to specific specifications and measurement methods.

According to Jérôme Azé (2010), the nominal field plays a role of filter on the real world realized by the producer, which must be known by the future user.

Several European and global standardization groups have extensively tested and used all these criteria.

According to Ubeda (1997), standardization work has focused on proposals that are closely linked to the achievement of objectives that go beyond quality in order to address more global interoperability, sharing and reuse problems.

19. Components of spatial quality include

Before explaining in detail the seven quality components defined by the Data Quality Commission of the ICA (International Cartographic Association), we first introduce the notion of "nominal land".

Some of these components aim to measure the accuracy of data in relation to different notions such as geometry, semantics and actuality.

This accuracy measurement is done by comparing the data with the real world.

It is generally accepted to replace, in this comparison, the real world with a "nominal ground".

A common definition of the latter is: the image of the universe at a certain date, as perceived through the product specifications (and/or content) filter.

20. Semantic precision (accuracy attribute)

This is the difference between the value of an attribute in the dataset and its value in the nominal world.

It is a quantitative criterion that concerns the classification of objects, the codification of attributes and relationships between objects.

An attribute is a characteristic of a location, a set of locations or an element on the surface of the earth.

This feature may result from a measurement or interpretation.

In the same way as geometric precision, semantic precision is defined as the difference between a measurement and another measurement that is comparable and recognized to be more accurate (Ubeda, 1997).

This is a relative definition because it depends on the accuracy of the objects of comparison.

It also requires knowledge of more precise data, namely the nominal terrain (Michael F. Goodchild 2005).

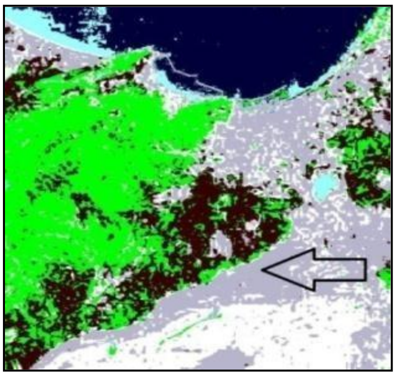


Figure-23: Example of semantic accuracy

21. Completeness (completness)

Indicates whether the objects in the nominal field are all represented in the dataset.

It is a quantitative criterion that answers the following questions (Mounir Azouzi, 1996) :

-Is the area completely covered?

-Is the number of objects modeled equal to the number of objects in the field?

-Do the modeled objects have the right number of attributes?

-Are all objects in the nominal field represented?

Completeness describes whether the objects in the dataset represent all geographic objects in the nominal terrain.

It also indicates whether each entity is represented and whether all object attributes are present.

The degree of completeness describes the extent to which the objects in the dataset represent all geographic objects in the nominal terrain (Mounir Azouzi, 1996) and (Ubeda, 1997)

22. Geometric accuracy, (spatial accuracy) or (positional accuracy)

Defines the degree of internal consistency of the data according to the specifications and modeling rules of the dataset.

It includes geometric coherence and topological coherence of spatial data (Mounir Azouzi, 1996)

It is a quantitative criterion that makes it possible to verify:

–if the geographic database objects meet the specifications,

–if the relations between objects are respected and if they comply with the specifications,

–if the topology is represented,

–if the variables used respect the predefined values.

Gives the position differences between the objects of the base and those of the real world. It is a numerical value that breaks down into two types (Mounir Azouzi, 1996):

- Position accuracy: The object is more or less well positioned on the map.

- shape accuracy: the shape of the object is more or less just on the map.

The purpose of this component is to account for the position differences between base objects and real objects, i.e., the nominal terrain (Ubeda, 1997).

23. Qualitative Criteria

I.6 News (or temporal precision)

determines the dates of the last update and the validity of the data. This is a qualitative criterion which allows answering questions such as:

- Is my data up to date?

- Which in a way informs the "freshness" of the data.

Examples of current images:

a) ImageTM2000 b)ImageTM2009

Figure I-24: Examples of current events

I.7 Genealogy (Lineage)

Describes the history of the dataset.

It is a qualitative criterion that traces the life of the dataset, from its creation to the provision of the user.

It provides information such as information on sources, data entry operations, data transformations, etc.

The genealogy component is in the form of a quality report containing a description of the acquisition processes (including the materials used), as well as the derivation methods (extrapolation, etc.).

The purpose of this component may be seen differently by the data producer and the data user (Ubeda, 1997):

- Producer: ensure standards are maintained.
- The user: knows the data that they possess will respond to their needs.

I.8 Temporal accuracy

This component is responsible for managing data observation dates, update types and validity periods.

Depending on the type of phenomenon observed, time management will be different. It then appears that time management requires keeping a large amount of information and dates (change dates, observation dates, effective update dates on the database).

This is a component for which there is no measure of recognized and accepted quality.

I.9 Internal quality

is the set of properties and characteristics of a product or service that give it the ability to meet the content specifications of that product or service.

It is measured by the difference between the data that should be produced and the data that was actually produced.

It is linked to the specifications of the nominal land (and in particular to the errors that can be made during the production of the data) and is evaluated according to the producer.

Internal quality can be translated as "How do I measure the quality of my data and how do I communicate it?"

It is measured on the basis of the criteria cited: geometric precision, completeness, semantic precision, logical coherence, timeliness, etc.

I.10 External quality

is defined as the adequacy of the specifications to the user's needs.

It is measured by the difference between the data desired by the user and the data actually produced.

It is related to the needs of users and therefore varies from one user to another.

Rather, it is defined as a fit for purpose that can be summed up as "What are the users' needs in terms of quality data and information and how can I offer them to avoid misuse of that data?"

This approach, which the English-speaking world summarizes by the expression «fitness for use» and which can be translated as «employability» creates a more direct link between data sets and their possible uses, between producer concerns and the expectations of most users.

But external quality remains more difficult to define given the multiple and varied needs.

24. Viewing Quality

The quality thus modelled must then be presented to the user.

This is of paramount importance in relation to certain processes such as decision-making processes [Veregin 95].

There are two important and complementary aspects:

How to present the quality?

The visualization of quality must meet criteria of readability and comprehension allowing any type of user to understand it.

Information must also be directly accessible, for example through the use of signs and symbols that are meaningful to all, as advocated by the National Cener for Geographic Information and Analysis (NCGIA).

Such an approach also helps to overcome the language problem.

When to present the quality?

Presenting all the quality information permanently on a map would lead to an unreadable result.

To remedy this problem; Sami Faïz (Faïz 96) proposes two approaches leaving the user the choice of the quality he wants to observe and how he wants to see it materialized.

The latter must therefore be aware of what is an acceptable quality with respect to its application, and how it is quantified. The two approaches are:

- To obtain quality information on an object: the end user chooses the criteria to be observed, the threshold of acceptability, the type of visualization (example: the orange color for an average quality) and the possible sub-criteria quality (an attribute, a date, a consistency rule, etc.).

- To obtain all the objects corresponding to a certain quality:

the user defines the target object class, the area to be studied, the value or the quality interval of interest.

With regard to quality related to adequacy, the classic approach is to present quality when it is insufficient (compared to needs) and not when it is good.

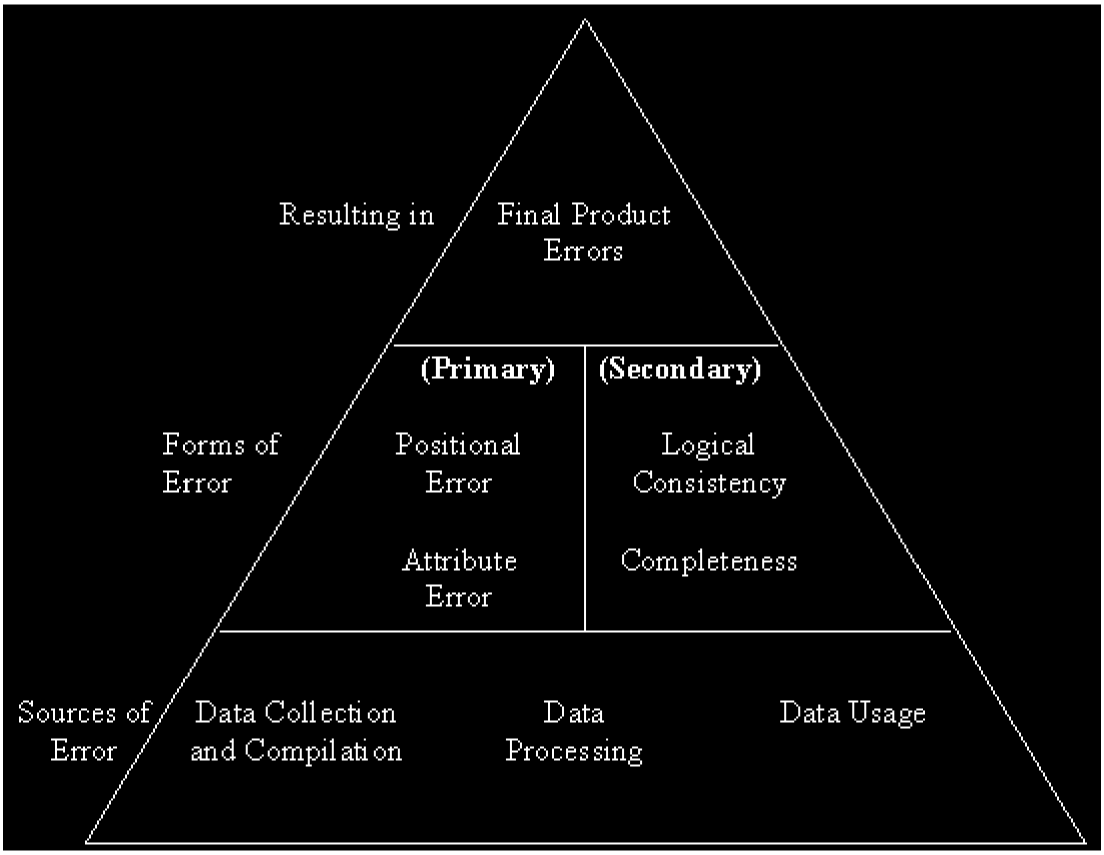


Figure I-25 : A classification of error in Geographic Information Systems (Hunter and Beard 1992)

25. *Chapter Synthesis*

It is important to be aware that manipulating information from a given source represents a first non-trivial problem.

In this first chapter, we have presented several formalisms that allow representing the uncertain information possessed by a source about the world.

In the next chapter, we will address the problem of information fusion, which can be considered as an extension of the classification problem.

In this chapter, we also present various existing fusion methods using formulas related to fuzzy logic.

Chapter 2: Strategies of the study

26. INTRODUCTION

The perspective we adopt in this study is not to challenge the traditional tools of classical classification methods, which have proven their effectiveness, for example in identification and mapping in remote sensing.

However, it should be noted that assessing the success of this type of classification goes beyond the framework of the so-called virtuous triangle (time, cost, quality) to be based on much broader consequences, particularly in terms of improving knowledge.

However, we assert that classical classification approaches often did not take into account the concept of uncertainty.

They are no longer sufficient on their own to guarantee the conditions for successful classifications.

They must be integrated into more comprehensive "fusion" approaches, based on identification and understanding of acquisition processes, aiming to integrate both uncertainty and technical aspects of discrimination.

To demonstrate the significance and contribution of the methods we have developed in improving spatial and spectral resolution, we have proposed to evaluate the results qualitatively and quantitatively.

27. DATA SETS

In the context of our study, we have various data sets used to test the established processing chain.

We have chosen urban areas with a high density of roads and buildings where we will test the various envisaged scenarios.

28. Study Area

The city of Oran , nicknamed 'Al Bahia,' which means 'The Splendid' or 'The Beautiful' ,is the second largest city in Algeria.

It is located in northwestern Algeria.

It is a port city covering an area of 2,114 km2.

The municipality alone has over 850,000 inhabitants, while the Oran agglomeration has over 1,453,150 inhabitants.

29. *Image data used*

For the study area, we have the following images:

Table II-1: The image data used.

Capteur	Channels used	Date d'acquisition	Résolution (m)
Quick- bird Panchromatique	0.45-0.9	2008	**0.6**
Quick-bird-Multi-spectrale	0.45-0.52 0.52-0.6 0.63-0.69 0.76-0.89	2008	**2.4**
Spot5	0.5-0.59 0.61-0.69 0.79-0.89 1.6-1.7	2004	**2.5**
TM	**0.45-0.51** **0.52-0.60** **0.63-0.69**	**2011**	**30**

30. *TESTING*

To implement the proposed approach 04 steps are outlined as follows:

1. Classification of Quick-bird multispectral images:

   Three types of classifications:

   Supervised classification, unsupervised classification, and fuzzy classification.

2. Application of low-level multi-sensor fusion techniques on THRS multispectral Spot and Panchromatic Quick-bird images.
3. Application of hybrid fusion between images from part 'A' and the classified image in part 'B'.
4. Accuracy evaluations.

31. *Data Normalization*

I.11 Geometric Normalization

It is crucial that the images are perfectly aligned, meaning that each pixel in both images refers to the same geographic area.

Several studies have been conducted on the influence of registration errors on the quality of results; therefore, the images were overlaid pair wise to monitor the geometric quality with coincidence on linear details.

I.12 Radiometric Normalization

Consists of scaling the data to a common scale before aggregation.

For example, during Boolean aggregation, the data must be expressed on a Boolean scale (0 and 1).

The main advantage of standardization is that it allows including variables measured on non-comparable scales in the same classification. Multi-sensor data must be standardized due to variations in radiometry caused by changes in atmospheric conditions.

To ensure that changes in atmospheric conditions are not interpreted as changes in landscape, a relative reluctance is calculated for each spectral band by dividing the radiometric values by the mean radiometric values of the image.

To refine this standardization, we adjust the histogram of one of the two images so that it resembles the histogram of the other image.

This function synchronizes the mode and maximum values of both histograms (Benjdia , 2008)

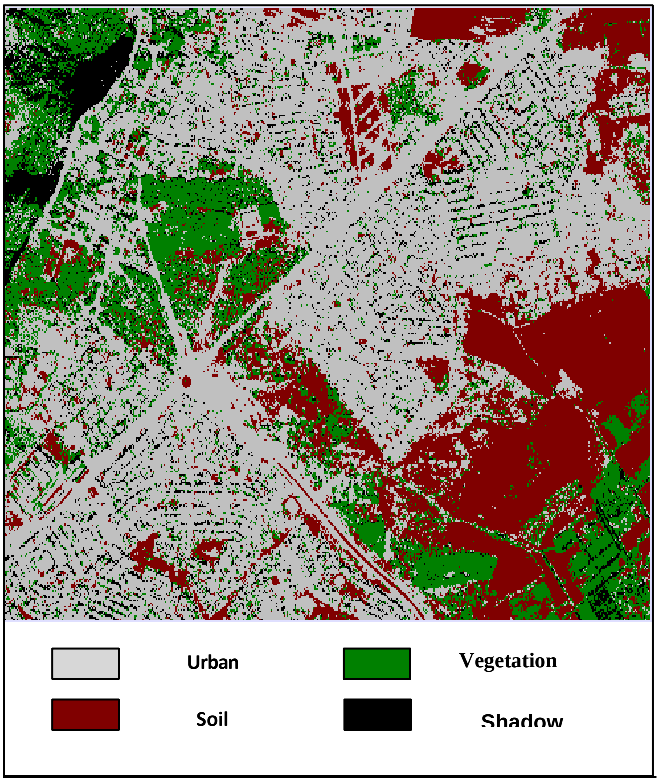
There are several methods for radiometric normalization.

The technique used in our study is the "Mean - Standard Deviation" calibration method.

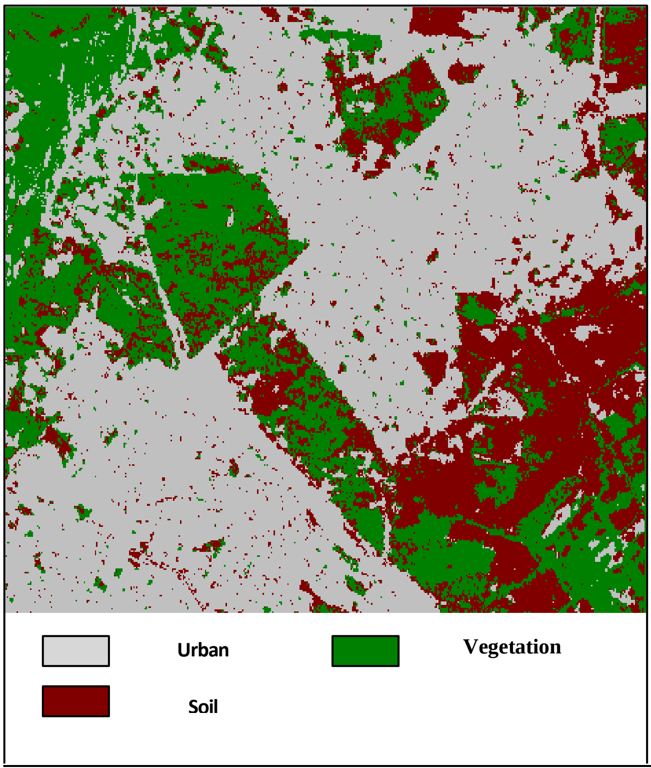
The result of this process for zone 1 is presented in the following table:

Table II-2: Statistics of Spot images before and after radiometric normalization.

Image	Reference «Quick-Bird»		Spot before normalization		Spot after Normalization	
Values	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Bande1	132.599	72.540	165.338	72886	133.072	71.975
Bande2	126.550	71.511	165.991	69.656	127.636	69.576
Bande3	120.994	72.707	158.888	75.448	121.750	70.832



a)Quick-bird



b) spot 5

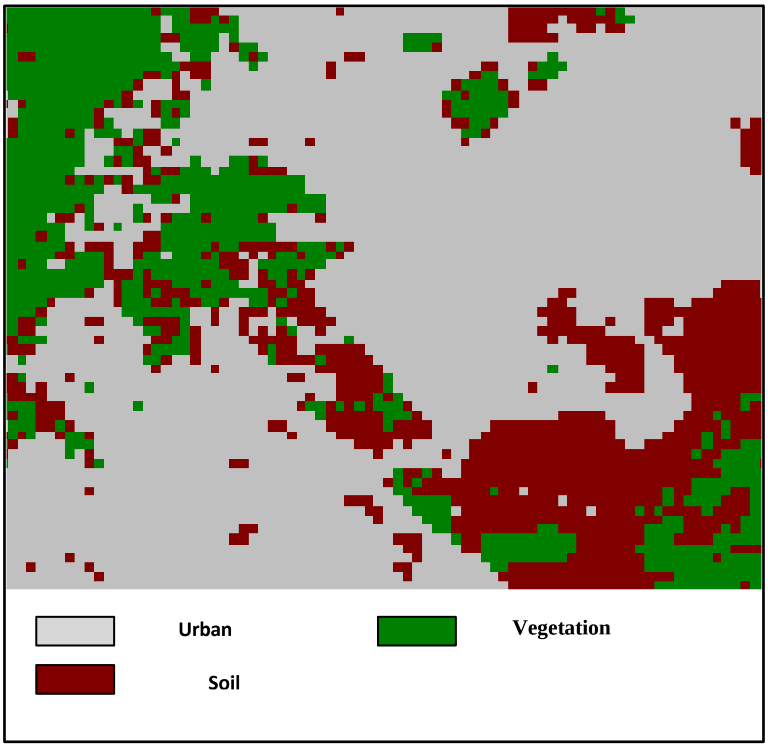


Figure II-4: Supervised Classifications (Maximum Likelihood)

The classification using the Maximum Likelihood method on the Quick-Bird image yielded a Kappa coefficient of 0.6235.

For the Isoclust method, the obtained Kappa was 0.3097.

For the K-means method, a Kappa coefficient of 0.2606 was achieved.

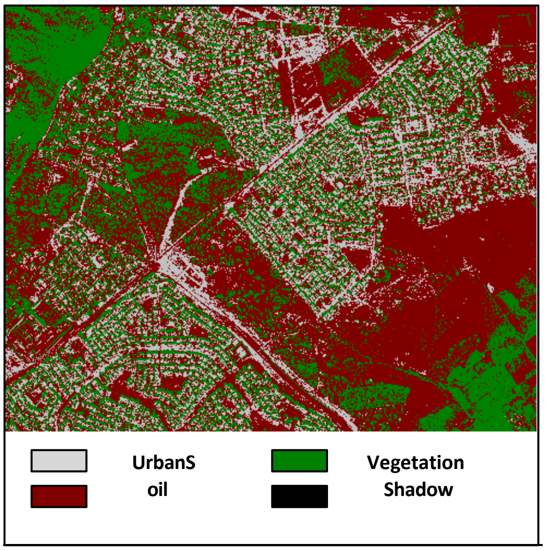


Figure II-5: Isoclust Classification

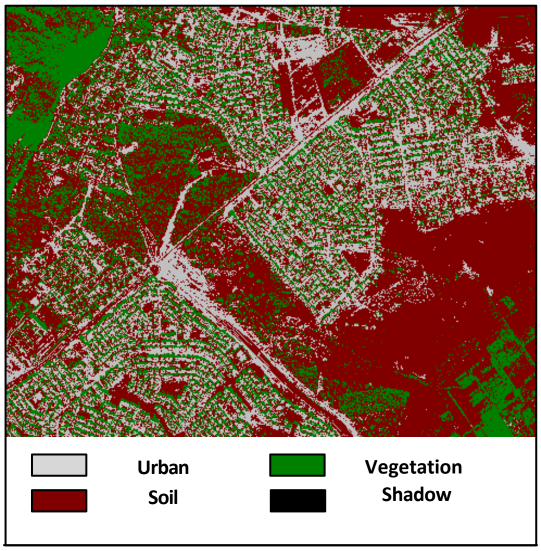


Figure II-6: K-means Classification

32. Classification based on fuzzy logic

Creation of fuzzy signatures:

After vectorizing the training parcels and assigning weights to each class (see Table II-3), fuzzy signatures are generated.

Table II-3: Partition Matrix of Signatures

	Urban	Soil	Vegetation	Shadow
Urban	0.841	0.118	0.040	0.001
Soil	0.104	0.831	0.065	0.000
Vegetation	0.178	0.123	0.696	0.004
Shadow	0.499	0.013	0.319	0.168

Fuzzification of classes:

This step involves creating fuzzy masks for each class using the fuzzy signatures .

Figure II-7: Fuzzy Mask of Urban Areas

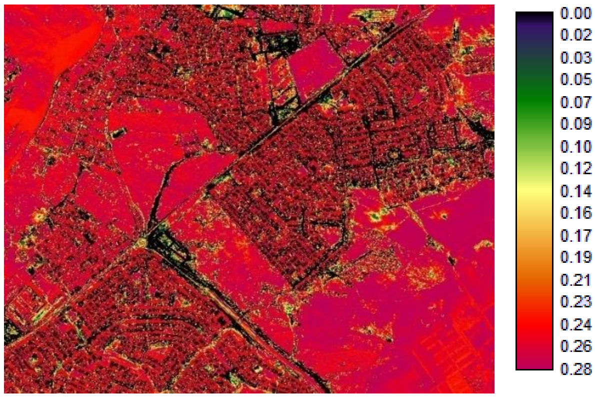


Figure II-8: Fuzzy Mask of Soil

Figure II-9: Fuzzy Mask of Vegetation

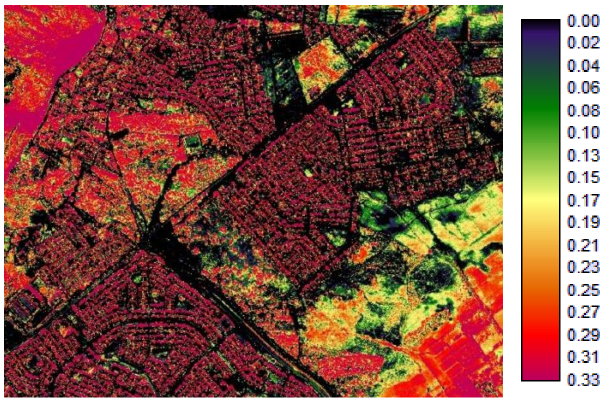
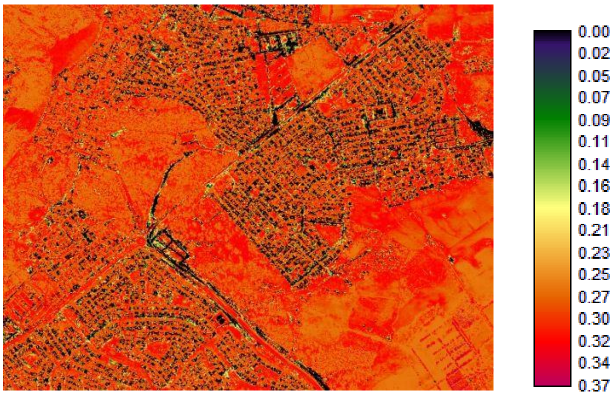


Figure II-10: Fuzzy Mask of Shadow



I.13 Defuzzification

We performed a " defuzzification " using 3 z-score values: 1.30, 1.96, and 2.58, corresponding to confidence thresholds of 0.1, 0.05, and 0.01 respectively.

It was observed that from 1.96 onwards, the results remained the same.

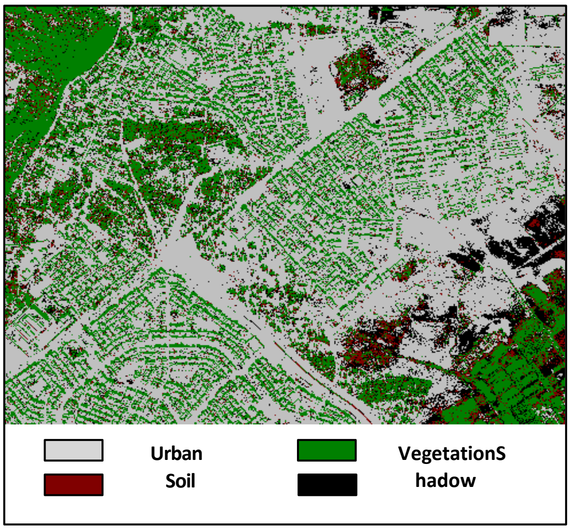


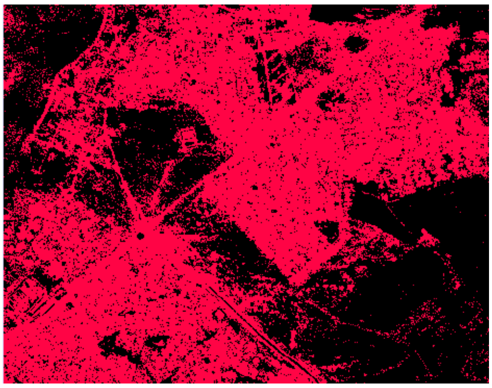
Figure III-11: Result of Fuzzy Classification

1) Improvement of classification through shadow removal:

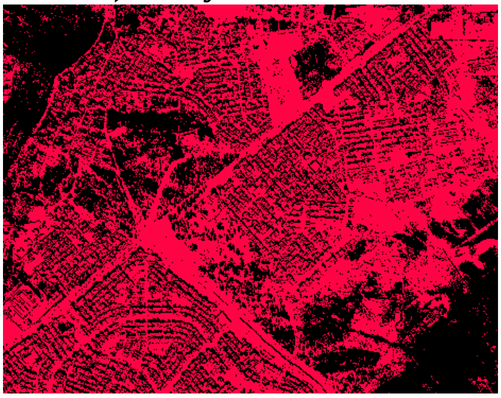
Before the class weighting step, shadows are eliminated using a TM image classification of the same area.

33. Extraction of "factor" images

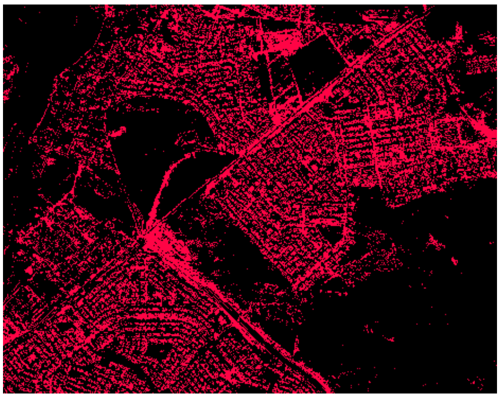
a) MSVB



B)Fuzzy



c) Isoclust



d)Kmeans

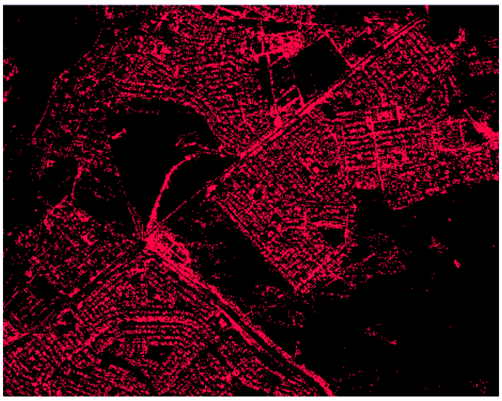


Figure II-13: Urban Masks

34. Estimation of weights:

To determine the weights of each mask, we created a preference table considering the accuracy of the user and the classifier.

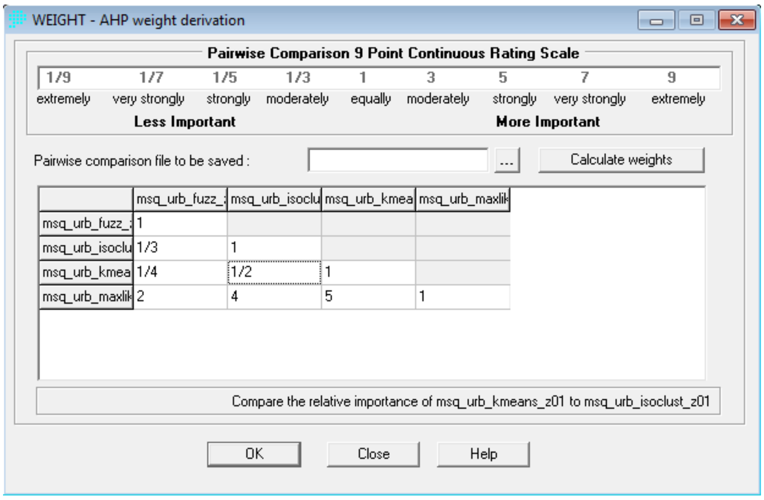


Figure II-13: Preference Matrix

Using the Analytic Hierarchy Process (AHP) based on Saaty's scale, we calculate the weights of each class.

Table II-4: Class Weights (Urban)

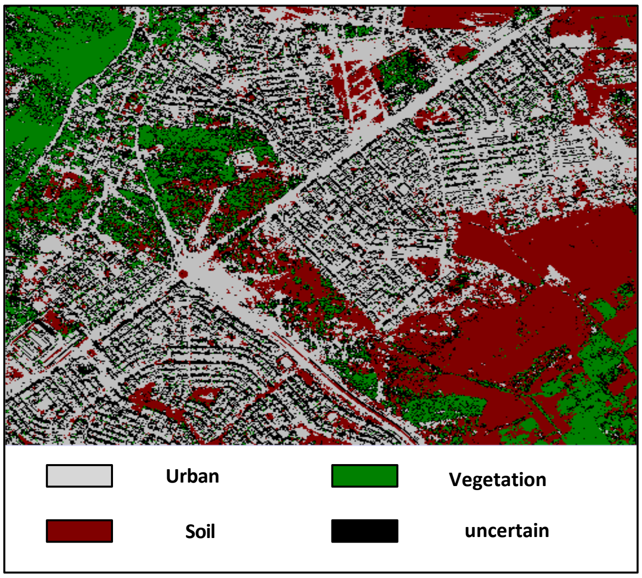
Classifier	Weights
MSVB	0.4918
Fuzzy	0.3056
Isoclust	0.1248
Kmeans	0.0778

35. 4Multi-criteria Classification

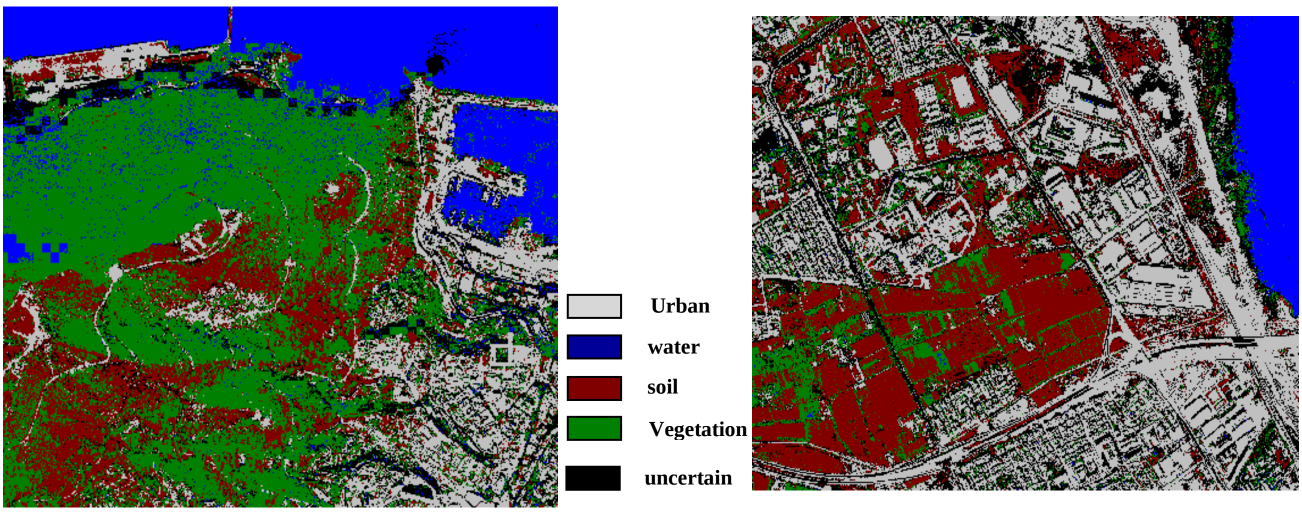
After determining the masks and their weights, fuzzy masks for each type of object are generated.

36. Combining Masks:

Using the fuzzy masks obtained in the previous step, we defined a threshold for assigning well-classified pixels to each thematic class. This process was applied to other areas as well (Figure II-16).



a) Zone 1



b) C)

Figure II-16 : Multi-Criteria Evaluation Classifications

37. HYBRID FUSION

By applying low-level fusion techniques and injecting the best technique classification "according to evaluation criteria" into the multi-criteria integration stage , we have applied 3 classic fusion methods:

I.14 IHS Transformation

This method is widely used; it involves transforming the RGB space of multi-spectral spot images to the IHS space and vice versa by returning to the old RGB space, replacing the intensity image with the Quick-Bird panchromatic image.

Figure II-17: Image fused using the IHS method

In Figure II.17, it is noted that the image resulting from the fusion of the Spot and Quick-Bird images shows

spatial improvement.

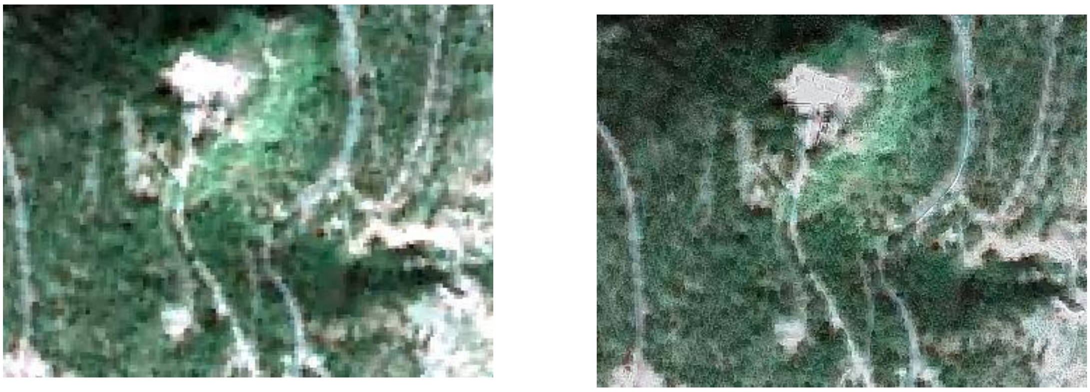
I.15 Fusion Brovey

This method involves creating fused images by applying mathematical operations on the raw images.

I.16 Fusion HPF

This method is simple but highly sensitive to registration errors.

Figure II-21: Image fused using the HPF method.



a) Extracted Spot Image **b) Extracted Fused Image using "HPF"**

Figure II-22: Comparison between Spot Image and HPF Image

- **Evaluationdesrésultats**

Table II-5: Evaluation Criteria of Different Fusion Methods

Zone 1 :

Method of Fusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	2.7964	-3.2643	0.537	0.5364	70.8217			
	1.7032	-4.3926	0.4299	0.4291	76.6362			
	-0.4448	-4.9448	0.5384	0.5372	70.7352	11.4385	57.0913	0.0328
Brovey	89.8554	46.7233	0.453	0.1659	110.599			
	84.5016	45.6342	0.4623	0.1722	104.8999			
	80.8293	46.5031	0.5336	0.1988	101.5827	16.5826	82.9576	0.0148
HPF	5.3069	41.5291	0.9255	0.6625	45.5793			
	-2.8189	40.8641	0.9174	0.6459	44.7884			
	-7.5085	40.7327	0.9289	0.6691	44.9587	7.0881	35.3843	0.0425

It is observed that the IHS method is stable in terms of means, standard deviation, and spectral angle mapper (SAM) angles between spectral signatures. On the other hand, the HPF fusion method is dominant for the values of correlation coefficient, ERGAS, and RASE .

38. *Effects of radiometric normalization on fusion*

There is a significant improvement in the quality of fused images, for example, the sharpness of the image due to the disappearance of noise grains (Table II-6). However, with respect to HPF fusion, no difference is observed between the two images.

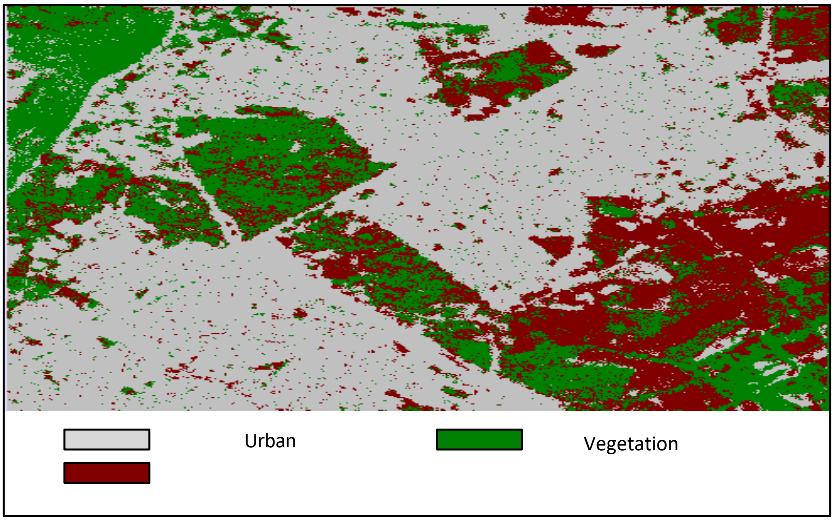


Figure II-24: MSVB Classification on the HPF Image

On the image presented above, we applied the processing from .

Weight estimation was carried out as for Zone 1.

Table II-7: Class Weights (Zone 1)

Classifier	Urban	Soil	Vegetation
MSVB	0.2728	0.4185	0.2923
Fuzzy	0.1732	0.0618	0.0528
Isoclust	0.0763	0.1599	0.1291
Kmeans	0.0506	0.0973	0.0810
MSVB(HPF)	0.4271	0.2625	0.4448

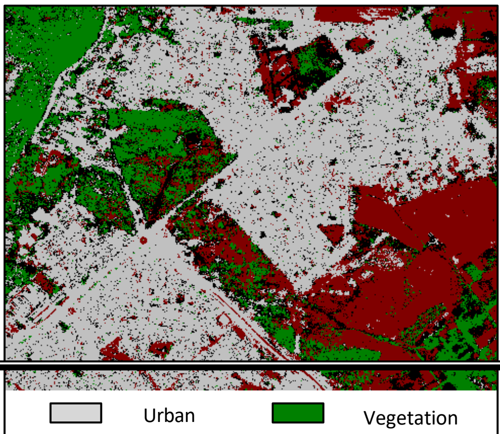
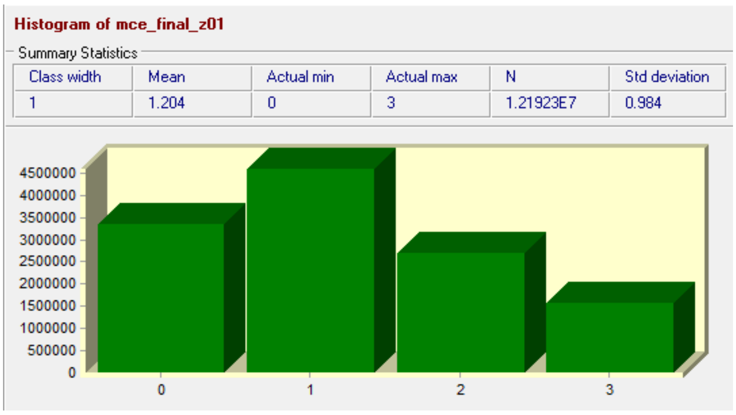
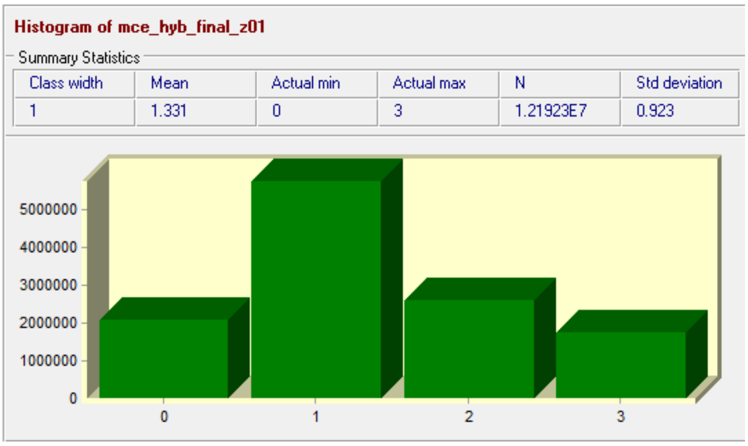


Figure II-24: Hybrid Multi-Criteria Evaluation Classification



a) MCE



b) MCE hybrid

Figure II-25: Comparison of histograms.

It is noted that the number of uncertain pixels has decreased.

Table II-8: Comparative study between different approaches.

39. *EVALUATION TOOLS*

I.17 Difference between Global Measures

Distances concern differences between global measures applied to a synthesized modality and its reference counterpart. These global measures can include the mean (M(Bk)), variance (V(Bk)), and standard deviation (σ(Bk)).

Bias (Bk, Bk*) = M(Bk) - M(Bk*). (Equation II-1)

The value of this distance is often given relative to the mean of the reference. Similarly, differences in variances, standard deviations, or entropies are divided by the variance (diffVarRel(Bk, Bk*)), standard deviation (diffσRel(Bk, Bk*)), or entropy of the reference modality. Ideal values for each of these distances are 0.

I.18 Correlation

This category includes distances that measure similarities between small-scale structures of the raw and fused images Bk*(i, j) and Bk(i, j). The correlation coefficient (cc(Bk, Bk*)) is the most well-known among them.

cc(Bk, Bk*) = M(Bk)*M(Bk*) / (σ(Bk)*σ(Bk*)). **(Equation II-2)**

I.19 Q Index

The Q index (proposed by Wang and Bovik, 2002) delivers values within the interval [-1, 1]. An ideal value of 1 is achieved when Bk* perfectly coincides with Bk.

Q(Bk, Bk*) = cc(Bk, Bk*) * (2 * M(Bk)*M(Bk*)) / (M(Bk)^2 + M(Bk*)^2 * σ(Bk)^2 + σ(Bk*)^2). **(Equation II-3)**

I.20 Distance between Spectral Signatures

The Spectral Angle Mapper (SAM) distance is becoming a standard in the field. SAM is the absolute value of the average angle between the spectral vectors of the fused image and the reference.

SAM((B, B*)) = arccos[(⟨Bk*(i, j)|Bk(i, j)⟩) / (‖Bk*(i, j)‖ * ‖Bk(i, j)‖)]. (Equation II-4)

I.21 RMSE (Root Mean Square Error)

Distances in this category are applied to the difference image between Bk* and Bk calculated at each pixel (i, j).

RMSE(Bk, Bk*) = 1 / nbPix * √(Σ(Bk*(i, j) - Bk(i, j))^2). **(Equation III-5)**

I.22 Global Distances

This category gathers distances that attempt, through a single measure, to provide an idea of the overall quality for the set B0* of fused MS modalities. An initial improvement to this distance was defined later by Wald (2000, 2002): it is called Relative Average Spectral Error (RASE). Its formulation is as follows:

$RASE$(Bk,Bk*) = 100 * √(1 / RMSE(Bk,Bk*)^2). **(Equation II-6)**

Where M corresponds to the average of N reference MS modalities. RASE returns a percentage value where the ideal value is 0. It characterizes the average performance of a method across the considered modalities. It's worth noting that no adjustment regarding scale is applied, making this measure sensitive to spatial resolution and the ratio between original images. These drawbacks were addressed with the development of a new measure named ERGAS, which stands for Adimensional Global Relative Synthesis Error (Wald 2000, 2002). Its calculation relies on the following expression:

$ERGAS$(Bk,Bk*) = 100 * √(1 / N * ∑(RMSE(Bk,Bk*)^2 / M(Bk))). **(Equation II-7)**

40. *Test Results of Evaluation Criteria*

We have implemented these criteria in a program that takes as input the two images to be compared, as well as their resolution, which is mandatory for ERGAS calculation. This program outputs two tables related to the calculated criteria (Figure II-26), and the results are shown in Table II-9.

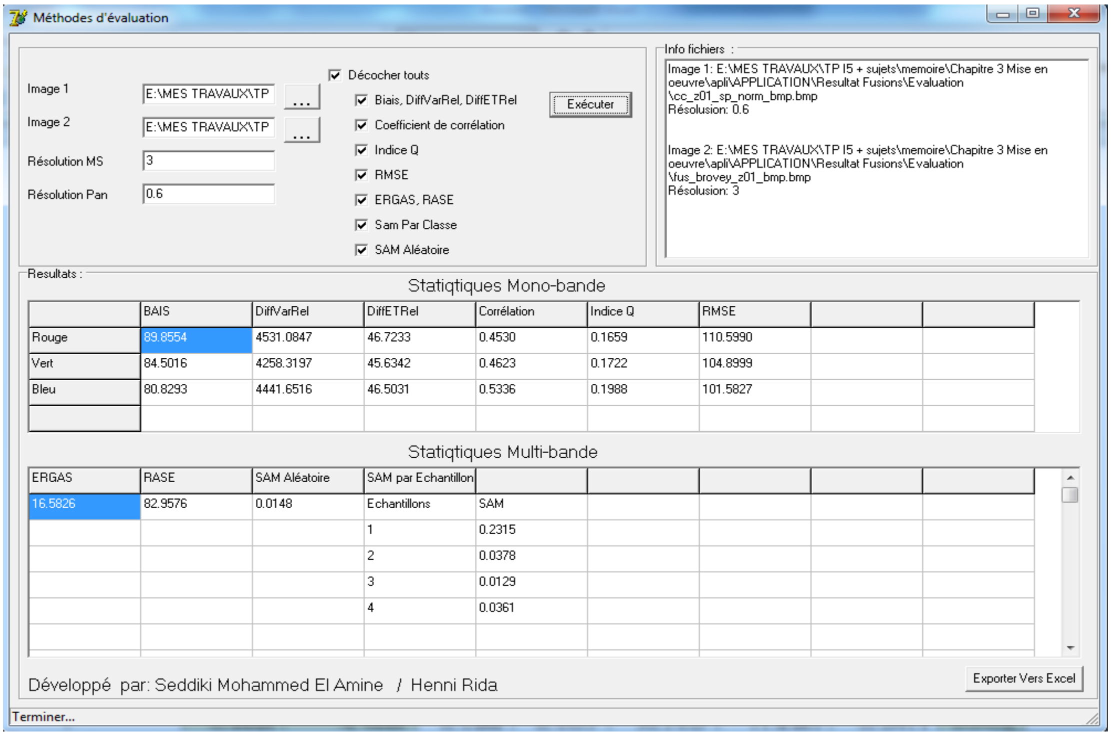


Figure III-27: Menu of the realized programmer

Zone1:

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	2.7964	-3.2643	0.537	0.5364	70.8217			
	1.7032	-4.3926	0.4299	0.4291	76.6362			
	-0.4448	-4.9448	0.5384	0.5372	70.7352	11.4385	57.0913	0.0328
Brovey	89.8554	46.7233	0.453	0.1659	110.599			
	84.5016	45.6342	0.4623	0.1722	104.8999			
	80.8293	46.5031	0.5336	0.1988	101.5827	16.5826	82.9576	0.0148
HPF	5.3069	41.5291	0.9255	0.6625	45.5793			
	-2.8189	40.8641	0.9174	0.6459	44.7884			
	-7.5085	40.7327	0.9289	0.6691	44.9587	7.0881	35.3843	0.0425

Zone2:

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	-0.3377	-0.1102	0.6566	0.6566	52.4142			
	0.9067	-3.1092	0.6858	0.6849	49.6841			
	0.9125	-4.4856	0.719	0.7171	46.9511	14.2506	71.3217	0.0095
Brovey	46.8772	42.2666	0.6338	0.2314	70.3731			
	47.7276	40.3613	0.7045	0.2549	68.1994			
	44.868	39.4701	0.7289	0.265	65.1504	19.4801	97.4339	0.0108
HPF	-23.9415	31.802	0.962	0.7355	41.6553			
	-27.1093	29.3958	0.9637	0.7481	41.7003			
	-29.5487	28.4908	0.9638	0.7438	42.6917	12.0778	60.2582	0.03

Zone3:

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	6.6525	-7.2747	0.6801	0.6747	53.206			
	-2.5918	-1.8121	0.5213	0.521	61.1063			
	-1.4137	-2.3846	0.6576	0.6571	54.542	9.9968	49.8842	0.0291
Brovey	75.3413	36.6394	0.6603	0.2934	89.8704			
	37.7694	22.7617	0.5757	0.4791	62.9573			
	14.1118	10.498	0.6596	0.6431	51.8864	12.2388	61.9919	0.3232
	7.2381	29.316	0.9569	0.7868	32.94			

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
HPF	-4.8008	35.3284	0.9405	0.6768	38.2407			
	-4.0498	35.4983	0.9536	0.7141	38.0961	6.4924	32.2965	0.0418

Zone4:

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	19.7385	-11.9558	0.7208	0.6914	46.0372			
	-9.1772	-4.2649	0.3585	0.3557	55.1231			
	-3.6394	-2.1341	0.5159	0.515	48.5459	10.2082	49.5995	0.099
Brovey	86.0498	29.6775	0.6128	0.2036	94.5994			
	60.8102	29.9043	0.4502	0.1856	73.4135			
	55.0211	32.2898	0.578	0.2204	68.6412	15.6246	78.9717	0.1573
HPF	11.2763	20.4368	0.9476	0.8121	26.094			
	-26.4206	25.5212	0.9036	0.6499	39.0888			
	-28.4158	25.2754	0.9297	0.692	40.008	7.4905	35.3145	0.1825

Zone5:

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	2.6863	-6.064	0.6154	0.6129	61.8339			
	2.4586	-3.8051	0.4307	0.4299	71.1563			
	-1.894	-5.0485	0.5682	0.5666	64.0799	10.3941	51.7622	0.0395
Brovey	91.5688	43.6969	0.5402	0.1939	108.3545			
	37.4605	20.0512	0.51	0.4491	68.0717			
	13.9893	8.2921	0.589	0.5793	58.4731	12.5214	63.8884	0.368
HPF	3.1519	35.6769	0.9388	0.7211	39.257			
	-11.2252	37.2997	0.9242	0.6612	42.2555			
	-15.7654	36.3903	0.9386	0.6978	42.6086	6.5514	32.5636	0.0625

Zone6:

Method defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	-1.9105	-7.034	0.6584	0.6537	49.49			
	1.9796	-0.4547	0.5069	0.5068	56.8534			
	0.3317	-4.2055	0.691	0.6893	47.8066	8.6632	43.2941	0.0279
Brovey	60.6554	27.4042	0.6505	0.4147	74.4177			
	37.1784	19.565	0.6081	0.5208	58.6209			
	27.5579	13.1803	0.6641	0.6217	52.1056	10.5014	52.4416	0.1792
HPF	5.7499	29.3016	0.9464	0.7326	32.4079			

	8.6247	31.8443	0.9366	0.6898	35.6387			
	10.2486	31.2937	0.9476	0.7219	35.3719	5.7965	28.9874	0.0166

zone7:

Méthode defusion	Bais	DeffETRel	CC	Q	RMSE	ERGAS	RASE	SAM
IHS	2.0143	-4.5216	0.5106	0.5095	68.8159			
	0.7826	-4.8532	0.4063	0.4052	72.4983			
	-1.4743	-5.1275	0.5044	0.5029	67.8927	12.1118	60.4509	0.0224
Brovey	75.7881	40.7324	0.4588	0.2046	96.5591			
	39.512	21.1547	0.441	0.3749	71.2286			
	16.2778	9.8411	0.5256	0.512	61.7814	13.3399	67.5173	0.3074
HPF	1.9108	37.4132	0.9088	0.6729	42.0438			
	-10.6049	36.2562	0.9004	0.6546	42.1969			
	-12.9538	36.6813	0.9137	0.6691	42.8804	7.368	36.7184	0.0588

Table II-9: Tables of evaluation results

41. SYNTHESIS OF THE CHAPTER

This third chapter is dedicated to the application of the preprocessing and processing chain developed to highlight new possibilities for remote sensing data analysis.

The objectives of this chapter were thematically focused on evaluating the performance of the developed method using new evaluation tools on a case study in a heterogeneous environment (Oran urban area). Furthermore, its results also highlight that new methods incorporating imperfections are better suited to reality.

The methods implemented make an additional effort in considering several factors for future applications, such as complementarity , redundancy, and source imperfections.

Chapiter3 Implementation results and evaluation

42. INTRODUCTION

On-demand mapping allows for the generation of cartographic products based on user needs.

Whether maps are produced online or offline, in real-time or within a few days, and whether the products are in paper or digital format, is of little importance. The main characteristic lies in the fact that the user specifies when and how the map should be produced.

Thus, a paper map is created upon request and according to user specifications.

Our study aims to dynamically represent a thematic map "result of classification," which must also adhere to the standards of classical cartography.

43. DISCRETIZATION OF RESULTS

The results of the classification include the classifications themselves and various evaluations (uncertainty maps).

In this section, we tested several methods of data discretization produced by quantitative analysis with the objective of varying the value of a symbol to represent the order (relative hierarchy) among objects and evaluate the effects on the resulting visualization.

Based on our literature review, we selected three discretization methods suitable for our dataset.

44. Standardized Discretization

This method involves discretization based on mean and standard deviation. Two types can be distinguished within this method: the first type frames the mean, and the second type encompasses the mean.

From these two types, we obtained the partitioning illustrated in the two tables below.

[Min	;M-2* σ	[;
[M-2* σ	;M-1 * σ	[;
[M-1 *Moy	; σ	[;
[M	;Moy+1* σ	[;
[M+1 * σ	; MȲ+2 * σ	[;

Discretization bounding the mean

[Min	;M-2* σ	[;
[M-2* σ	;M-1 * σ	[;
[M-1 *Moy	; σ	[;
[M	;Moy+1* σ	[;
[M+1 * σ	;MȲ+2 * σ	[;

Discretization encompassing the mean

Table III-2: Discretization encompassing the mean

Classes	Thresholds		Number of pixels
1	0.00	6.92	318107
2	6.92	28.46	634900
3	28.46	50.00	217197
4	50.00	71.54	1597205
5	71.72	93.08	4066441
6	93.08	100.00	181867

Classes	Thresholds		Number of pixels
1	0.00	28.46	953007
2	28.46	39.23	8248
3	39.23	60.77	517340
4	60.77	71.54	1288814
5	71.54	100.00	4248308

45. Discretization bounding the mean

We can observe that the relative frequencies of the classes calculated by the method that bounds the mean are balanced. On the other hand, the second method results in classes with unbalanced frequencies.

46. Discretization according to nested means

This is an iterative approach:

-Calculation of the first-order mean moy1 over the entire distribution

-Partition into two subsets [minimum; moy1]

]moy1; Maximum[

This operation can be iterated indefinitely.

Table III-3: Discretization according to nested means

Classes	Thresholds		Number of pixels
	0.00	12.50	318265
2	12.50	25.00	498298
3	25.00	37.50	144603
4	37.5	50.00	209038
5	50.00	62.50	314561
6	62.50	75.00	2047405
7	75.00	87.50	3301680
8	87.50	100.00	181867

This method has provided a good partitioning of class frequencies with fairly close ranges.

The number of classes is determined by the user.

III-2-3. Mathematical discretization

This involves partitioning classes with equal intervals.

It characterizes classes with constant steps containing a variable number of statistical units.

Table III-4: Mathematical discretization

Classes	Thresholds		Number of pixels
1	0.00	14.28	318265
2	14.28	28.56	634742
3	28.56	42.84	173050
4	42.84	57.12	185892
5	57.12	71.40	1455460
6	71.40	85.68	4066441
7	85.68	100.00	181867

It is noted that it does not take into account the frequency of values with a predefined number of classes at the beginning of the calculation.

The illustrations of the different techniques are presented in the following section:

Image obtained through discretization using the standardized method "Bounding the mean."

III-3. CREATION OF CARTOGRAPHIC VISUALIZATION

47. Choice of Development Environment

Initially, digital information production was static, limited to simple bitmap format maps like BMP and JPEG on one hand, and user requirements on the other. The introduction of animated formats like GIF and PNG brought a new concept of animating maps.

A dynamic map can be created using any programming language with image processing capabilities, but it is limited to raster graphics.

By the end of 1999, a promising new standard emerged: SVG (Scalable Vector Graphics).

It introduced the ability to integrate vector graphics into websites. The interest shown by major IT players suggests that widespread adoption of this technology is imminent.

This will undoubtedly benefit cartographers, who for the first time in web history will be able to meet demands for complex graphical representations.

SVG is an XML-based grammar for describing two-dimensional graphical objects.

It allows management of three types of graphical objects: vector shapes (curves, lines, polygons, etc.), text, and raster images.

SVG provides extensive capabilities for creating maps to be published on the internet and mobile devices.

Objects can be grouped, transformed, and styled, and SVG handles events such as "onclick" and "onmouseover" for each graphical object, enabling animations (e.g., displaying a tooltip when hovering over an object) using scripting languages like JavaScript or ECMAScript. SVG files can be viewed in web browsers with the addition of a specialized plugin.

By publishing SVG specifications as an official recommendation, W3C certifies the stability of the specification, its contribution to web interoperability, and advocates for its adoption.

After a year of refinement, SVG 1.0 attained the status of an official recommendation. This open format for vector images and animations on the web is based on XML standards.

According to W3C, SVG "primarily serves dynamically created graphics oriented towards databases."

Viewing SVG documents typically requires downloading a plugin (SVG Viewer) unless native support is integrated directly into browsers.

More than just an alternative to SWF (Shockwave Flash), SVG is integrated into XML architectures, utilizing CSS and XSL stylesheets, RDF metadata, XML Link hyperlinks, and SMIL Animation.

Other formats have also emerged, such as SVF (Simple Vector Format), DWF (Drawing Web Format), SWF (Shockwave Flash), VRML (Virtual Reality Modeling Language), and Java2D.

48. *SVG (Scalable Vector Graphics)*

SVG is a language for describing two-dimensional graphics in XML. It supports three types of graphical objects: vector graphic outlines (e.g., paths consisting of straight lines and curves), images, and text. Graphical objects can be grouped, styled, transformed, and composed into previously rendered objects. Its feature set includes nested transformations, clipping paths, alpha channel-based masks, and template objects.

49. *SVG and the Document Object Model (DOM)*

SVG drawings can be interactive and dynamic.

Animations can be defined and triggered declaratively (by embedding SVG animation elements within SVG content) or via scripting. Sophisticated SVG applications leverage scripting languages to manipulate the SVG Document Object Model (DOM), providing full access to all elements, attributes, and properties. A wide range of event handlers, such as `on mouse over` and `on click`, can be assigned to any SVG graphical object. Due to its compatibility with other web standards and the synergistic effects produced by them, functions like scripting can simultaneously affect XHTML and SVG elements on the same web page.

SVG is a standardized XML dialect for describing 2D graphics (vector graphics, text, and raster graphics).

Graphic styles, familiar from graphic design software, can be defined using CSS to uniformly style groups of graphical objects.

Similarly, it's possible to modify the appearance of multiple objects. Thanks to its styling language compatibility, SVG files can be seamlessly integrated into web documents.

50. *Integrating SVG into the DOM enables control* Application

and modification of SVG elements using familiar JavaScript/Java interfaces.

Regarding interactivity, SVG offers a rich palette of events (mouseover, mouseout, onclick, keypress, etc.).

These are employed similarly to traditional HTML elements. Each SVG element can be animated by modifying its attributes such as color, shape, opacity, position, etc. (Kaddour.H, 2007).

I.23 Developed Tools

The tools developed to obtain the dynamic map (Figure III-2)

I.24 Scrollbars:

This tool allows for effective navigation of the map by integrating the scrollbar into the SVG code.

This is achieved by assigning an ID to the map container and creating a variable of type "scroll".

I.1.1 Code SVG

```
<gid="content1">
<!--Lesvecteurimopterdesmasques-->
<g/>
```

Code Java Script:

```
//Créationd'unObjetdetypeScroll enidiquent l'IDsurlequelleScroll estappliqué
scrolledObject1=newscrolledObject("content1",Xmin,Xmax,Ymin,Ymax,
"sb1-horiz","sb1-vert");
```

• Clickable map:

With this tool, users can view the ground reality ("reference") of each thematic class by clicking on the selected class using the "On mouse down" event.

I.1.2 CodeSVG:

```
<!—
Onassocierl'évenementdeclickaunefonctionquirendretoutlesthèmestra
nsparentsauf laréalité terrain -->
<pathonmousedown="trans(evt)"d="m489.19588,...,-0.440983z"id="Eau"
/>
```

51. *Displaying information on the selected theme:*

A table of information "row, column, theme, number of pixels in the selected theme" is displayed when the user hovers over one of the themes on the map. This tool is developed using the "On mouse over" event.

CodeSVG:

```
<!—Sil'utilisateur
passeparlecurseursurundesthèmeslafonctionthèmeestexécutéquiapour rôle d'afficher le
tableau d'informations-->
<pathonmouseover="theme(evt)"d="m89.88,...,-0.123z"id="Urbain" />
```

• Production of a map with interactive legend:

- Displaying masks of each theme when the user hovers over the symbol of each theme.

- Users can show or hide different map themes by clicking on the radio buttons corresponding to each theme.

- A map of "uncertain pixels" created in section III-2 is displayed if the user clicks on the symbol of the uncertain class.

52. *SYNTHESIS OF THE CHAPTER*

In this application, we demonstrated the capabilities of cartographic representation using multimedia tools from remote sensing products. Our interfaces offer customizable data visualization, making exploratory tasks easier. An interactive legend enhances navigation, turning the map into a dynamic collection of "cartographic projects."

53. *CONCLUSION*

This thesis aims to develop methodologies for utilizing THRS data to characterize surface objects from various sources and dates. We focus on mapping land use in urban and suburban areas, which are ideal for testing our methods due to their heterogeneity and challenges. Our main goal is methodological, aiming to create suitable methods for these datasets.

We developed a processing pipeline based on fuzzy logic theory applied to remote sensing data and tested it on THRS images of Oran city. The pipeline and evaluation tools are designed to be replicable. Our results highlight the potential of novel visualization and mapping techniques in image classification, with numerous thematic applications benefiting from these advancements.

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