Abstract—Automatic methods of detecting changes through satellite imaging are the object of growing interest, especially because of numerous applications linked to analysis of the Earth’s surface or the environment (monitoring vegetation, updating maps, risk management, etc...). This work implemented spatial analysis techniques by using images with different spatial and spectral resolutions on different dates. The work was based on the principle of control charts in order to set the upper and lower limits beyond which a change would be noted. Later, a contrario approach was used. This was done by testing different thresholds for which the difference calculated between two pixels was significant. Finally, labeled images were considered, giving a particularly low difference which meant that the number of “false changes” could be estimated according to a given limit.

Keywords—multi-scale, a contrario approach, significant thresholds, change detection.

I. INTRODUCTION

Change detection is a vast subject, for which many methods have been proposed, notably by Coppin [1] and Lu [2]. These methods were classified by Ola [3] according to the level of intervention and which are broken down into the following:

- On the pixel level: analysis by change vectors, simple detectors and regression;
- On the characteristic level: texture analysis, principal components analysis, analysis of shape, difference vegetation index and wavelets;
- On the object level: methods of direct multi-date classification, post-classification comparison and fuzzy post-classification comparison, artificial intelligence, artificial neuron networks and expert systems.

Change detection means detecting and locating areas having evolved between two observations (or more) of the same place. These changes can be useful [4]:

- In tracking soil use, meaning the development of vegetation or the detection of seasonal changes in vegetation,
- In managing natural resources during urban development and deforestation, etc...
- In mapping out damages due to natural disasters such as volcanic eruption, tidal wave, earthquake or flood.

The contrario detection method is a new method in imagery. It was inspired by psychological research on vision in order to imitate the human brain. The mechanism of this detection was studied by psychologists whose conclusion indicated that the human brain locates, and then detects, events in an image [5].

The research initiated in the late 90s by Desolneux, Moisan and Morel [6] aimed at developing a quantitative theory for visual perception based on the Gestalt laws. A contrario detection consists of determining the threshold from which the a priori model is no longer the one observed, but obviously an event which is detected as a difference compared to the a priori model [7].

Despite the relevancy of their qualitative observations on perception, the Gestaltic school could not answer the quantitative questions to determine the threshold beyond which a geometric structure is drowned in noise and therefore no longer visible by our perception [8].

Spatial resolution is the size of a pixel on the ground and comparing two images having different resolutions becomes difficult.

The method of disaggregation of information as well as fusion methods like morphological pyramid or wavelet decomposition has all been used to solve the problem of multi-scale or multi-resolution analysis on remote sensing or in subpixelic analysis [9].

Robin is the first to have considered change detection and sub-pixel classification using satellite image processing to monitor continental surfaces over time. By using an a contrario probability criteria which measures coherence in the sequence of “low-resolution” images and a previous reference point represented by a high-resolution classified image, Robin defined the Number of False Alarms (NFA) associated with a sub-field where the change pixels thus correspond with a complementary field [9].
The limits presented by these methods can be found in the difficulty of choosing an a priori threshold and the sensitivity to the natural variability of observations from one year to another (shifting of the seasons, ...).

The work undertaken here was divided into two parts: multi-scale analysis and change detection based on an a contrario approach.

The question asked was the following: how can changes be detected in high and low-resolution satellite images based on Statistical Process Control (SPC) methods?

Moreover, the reasoning proposed for change detection in the low and high-resolution satellite images based on the a contrario approach responded to the question: at what thresholds the calculated difference between two pixels is significant?

II. METHODOLOGY

A. Data And Processing

Multi-scale analysis is a preliminary step or pre-processing of data for change detection because it allows us to detect changes occurring in several satellite images with different resolutions.

The data used for the multi-scale analysis was characterized by:
- Their spatial resolution which is the size on the ground of the pixels,
- Their spectral resolution which is the width of the spectral bands detected,
- Their temporal resolution which is the interval between two images of the same point and depends on the satellite’s orbit.

The images delivered by sensors with different characteristics distinguish geometric structures depending on spatial resolution [10].

This work played around with four images taken on different dates with different resolutions. Each image was segmented into six clusters. The images were classified according to the Expectation-maximization algorithm (EM) which is done by passing through [11]:
- An expectation step (E),
- A maximization step (M), where the maximum likelihood of the parameters is estimated by maximizing the likelihood found in step (E),
- The parameters found in (M) for a new phase of evaluating the expectation.

The method adopted for the multi-scale analysis is based on the principle of control charts. This principle consists of determining lower and upper limits. Limits were calculated according to the Expectation-maximization algorithm (EM) for a new phase of evaluating the expectation.

The following table gives a detailed description of the characteristics of the images used.

<table>
<thead>
<tr>
<th>Description</th>
<th>SPOT1</th>
<th>SPOT2</th>
<th>SPOT4</th>
<th>SPOT5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral bands</td>
<td>B1: 0.50-</td>
<td>B1: 0.50-</td>
<td>B1: 0.51-</td>
<td>0.49 -</td>
</tr>
<tr>
<td></td>
<td>0.59 μm</td>
<td>0.59 μm</td>
<td>0.59 μm</td>
<td>0.69 μm</td>
</tr>
<tr>
<td></td>
<td>B2: 0.61-</td>
<td>B2: 0.61-</td>
<td>B2: 0.61-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.68 μm</td>
<td>0.68 μm</td>
<td>0.68 μm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B3: 0.78-</td>
<td>B3: 0.78-</td>
<td>B3: 0.79-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.89 μm</td>
<td>0.89 μm</td>
<td>0.89 μm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B4: 1.58-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.75 μm</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date</td>
<td>1987</td>
<td>1998</td>
<td>June 2000</td>
<td>28 April 2003</td>
</tr>
<tr>
<td>Resolution</td>
<td>10 m</td>
<td>20 m</td>
<td>20 m</td>
<td>5 m</td>
</tr>
<tr>
<td>Pixel size</td>
<td>128X128</td>
<td>128X128</td>
<td>128X128</td>
<td>637X637</td>
</tr>
</tbody>
</table>

The study area chosen is located north of Tunis, bordered by a marsh named Sebkhet Ariana on the east and the Lake of Tunis and Tunis-Carthege airport on the southeast, extending to the northwest to the neighborhood of Soukra. This area is characterized by the heterogeneity of the environment, especially due to the presence of the marsh, a more or less high-traffic urban area, a green belt and streets. Table 2 gives a lexicon of the clusters present in the study area.

Due to the ease of interpretation and implementation, image differencing is without doubt the most widely used detector. Univariate image differencing (UID) consists of carrying out the differencing pixel by pixel between the original image \( I \) (or its transform) and image \( I' \) (or its transform):

\[
I_D(i, j) = I_1(i, j) - I_1(i, j)
\]

This method results in an image called the “differencing image” (DI), revealing changes having taken place between the two observations. The pixels from the DI image with high positive or negative values are likely to characterize changes, whereas those with near-zero values correspond to unchanged pixels [12].

B. Change detection based on the a contrario approach

The data used for a contrario change detection were limited to one multi-spectral image SPOT4 (256X256) dating from 2000 having a 20m resolution and to one panchromatic image SPOT5 (1024X1024) dating from 2003 with a 5 meter resolution. The model of observations in the absence of change is called the a contrario model. In this model,
significant changes are defined as being events of low probability of occurrence: an event is called \( \varepsilon \)-significant if the expectation of the number of occurrences of this event is less than \( \varepsilon \) in the a contrario model [13].

The a contrario approach consists of rejecting the hypothesis \( H_0 \) for the difference \( \text{diff} \) if the difference is \( \varepsilon \)-significant. The a contrario method is, in fact, linked to the standard framework of hypothesis tests.

The difference was calculated between two pixels from two low-resolution (LR) images coming from the averaged high-resolution (HR) image and from the real LR image.

The panchromatic high-resolution spatial (HR) SPOT5 image underwent averaging by regrouping the pixels according to a fixed threshold equal to ±2 \( \sigma \).

Knowing that these images were taken on two different dates \( t_1 \) and \( t_2 \).

\[
\text{diff} = \left[ \left| L_{HR_s}(i_t) - H_{LR_s}(i_t) \right| \right] \text{..........}
\]

\[
\text{diff} = \left[ \left| L_{HR_s}(i_t) - H_{LR_s}(i_t) \right| \right] \text{..........}
\]

\[
\text{diff} = \left[ \left| L_{HR_s}(i_t) - H_{LR_s}(i_t) \right| \right] \text{..........}
\]

\[
\text{diff} = \left[ \left| L_{HR_s}(i_t) - H_{LR_s}(i_t) \right| \right] \text{..........}
\]

Finally, the NFA was determined that was less than a \( \varepsilon \)-significant threshold so that:

\[
NFA(\{L_{HR}(i_t) - H_{LR}(i_t)\}) > \ldots > \varepsilon > ..
\]

\[
NFA(\{L_{HR}(i_t) - H_{LR}(i_t)\}) > \ldots > \varepsilon > ..
\]

\[
NFA(\{L_{HR}(i_t) - H_{LR}(i_t)\}) > \ldots > \varepsilon > ..
\]

\[
NFA(\{L_{HR}(i_t) - H_{LR}(i_t)\}) > \ldots > \varepsilon > ..
\]

\[
NFA(\{L_{HR}(i_t) - H_{LR}(i_t)\}) > \ldots > \varepsilon > ..
\]

At last, according to the results obtained, a map was established of the changes related to the HR SPOT5 and the LR SPOT4 images.

The same method was repeated but labeled images were taken into consideration and a \( \varepsilon \)-significant threshold was opted for. This threshold was chosen according to the control chart principle recommended in the SCP which is supposed to monitor, by statistical methods, the operational process or procedure.

Noting that if \( \mu_i \) is the typical average of each cluster \( c_i \), the difference between the estimated image \( H_{HR}(\mu_i) \) by \( \gamma \) and observed \( L_{HR_s}(i_t) \) can be measured by:

\[
diff = \left| L_{HR_s}(i_t) - H_{HR_s}(i_t) \right| \text{..........}
\]

\[
diff = \left| L_{HR_s}(i_t) - H_{HR_s}(i_t) \right| \text{..........}
\]

\[
diff = \left| L_{HR_s}(i_t) - H_{HR_s}(i_t) \right| \text{..........}
\]

\[
diff = \left| L_{HR_s}(i_t) - H_{HR_s}(i_t) \right| \text{..........}
\]

\[
diff = \left| L_{HR_s}(i_t) - H_{HR_s}(i_t) \right| \text{..........}
\]

Success in having a particularly low difference in a LR image allowed the number of “false changes” to be estimated according to a fixed threshold equal to \( \pm \sigma \). The map of changes could thus be extracted from this procedure.

A. Multi-scale analysis

Spatial analysis of the images was undertaken with different spatial, spectral and temporal resolutions. It was asserted that:
Each image was segmented into 6 clusters.

The results of the multi-scale analysis are illustrated by Figures 3 through 6 which show the images classified according to the EM method.

Fig. 3 Image SPOT1 classified (1987)

Fig. 4 Classified SPOT2 Image (1998)

Fig. 5 Classified SPOT4 Image (2000)

Fig. 6 Classified SPOT5 Image (2003)

Tables 3 through 6 give the average and standard deviation of each cluster.

| TABLE III AVERAGE AND STANDARD DEVIATION OF THE SPOT1 IMAGE (1987) |
|--------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
|                           | C1             | C2             | C3             | C4             | C5             | C6             |
| Average                  | 28.730         | 75.417         | 112.495        | 144.218        | 177.234        | 212.602        |
| Standard Deviation       | 17.294         | 12.516         | 17.095         | 17.335         | 15.219         | 18.803         |

| TABLE IV AVERAGE AND STANDARD DEVIATION OF THE SPOT2 IMAGE (1998) |
|--------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
|                           | C1             | C2             | C3             | C4             | C5             | C6             |
| Average                  | 102.603        | 122.079        | 150.098        | 172.816        | 183.991        | 211.301        |

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C1</td>
<td>C2</td>
<td>C3</td>
<td>C4</td>
<td>C5</td>
<td>C6</td>
</tr>
<tr>
<td>Average</td>
<td>26.466</td>
<td>68.084</td>
<td>107.702</td>
<td>142.572</td>
<td>178.339</td>
<td>220.274</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>14.062</td>
<td>17.689</td>
<td>16.400</td>
<td>15.649</td>
<td>15.917</td>
<td>20.007</td>
</tr>
</tbody>
</table>

| TABLE VI AVERAGE AND STANDARD DEVIATION OF THE SPOT5 IMAGE (2003) |
|--------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
|                           | C1             | C2             | C3             | C4             | C5             | C6             |
| Average                  | 13.273         | 51.280         | 101.676        | 146.924        | 182.403        | 224.227        |

Fig. 7 Detection of changes present in several multi-resolution satellite images for cluster according to the upper and lower limit method

Figures 7 through 12 represent change detection present in images I1, I2, I3 and I4 for each of the clusters: \{ cluster 1, cluster 2, cluster 3, cluster 4, cluster 5, cluster 6\} according to the upper and lower limit method. Indeed, the points outside the limits were considered to be changes.

Examination of Figure 7 compared to cluster 1 shows that there are two points which correspond to the image, I2 and I4, which are outside of the limits. Cluster 1 corresponds, in fact, to wetlands and changes in this area are highly variable.
Figure 8 presents only one point outside of the limits under consideration, corresponding to image I2 for cluster 2: bare soil.

Figures 9, 10, 11 and 12 correspond to categories 3, 4, 5 and 6 representing, respectively, vegetation, the green belt, roads and the urban area. They do not show any points outside the limits under consideration.

Tables 7 through 12 give, for each image, the average of each cluster and, as well, the average standard deviations $\bar{\sigma}_C$, the upper and lower limits beyond which there are changes and the proportion of considered cluster occupancy for each image.
The multi-scale analysis detected changes present in several satellite images with different resolutions by taking into consideration the upper and lower limits based on the control charts principle. Examining Table 13 shows a spatial-temporal variation of changes in the rates of land uses from 2000 to 2003, even if the multi-scale analysis carried out performed was only qualitative. The variations in clusters 1 (<-14.78%), 3 (<-2.36%) and 4 (<-2.38%) are understandable. In fact, land uses of the wetlands, vegetation and green belt, which correspond to clusters 1, 3 and 4, respectively, decreased, whereas there was an increase on the bare soil, roads and the urban area which correspond respectively to clusters 2, 5 and 6.

B. Change detection based on the a contrario theory

The results of applying the first advance are shown in Figures 13 to 21. Table 16 provides the rates of change of land uses depending on the thresholds $\varepsilon$.

![Fig. 13 Map of change for $\varepsilon=10^{-8}$](image1)

<table>
<thead>
<tr>
<th>Cluster 3</th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
<th>Mean Of The Averages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>112.495</td>
<td>150.098</td>
<td>107.702</td>
<td>101.677</td>
<td>117.993</td>
</tr>
<tr>
<td>Lower Limit</td>
<td>86.491</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper Limit</td>
<td>149.495</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Fig. 14 Map of change for $\varepsilon=10^{-7}$](image2)

<table>
<thead>
<tr>
<th>Cluster 4</th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
<th>Mean Of The Averages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>144.218</td>
<td>172.816</td>
<td>142.572</td>
<td>146.924</td>
<td>151.633</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>17.335</td>
<td>9.903</td>
<td>15.649</td>
<td>18.507</td>
<td>15.349</td>
</tr>
<tr>
<td>Lower Limit</td>
<td>120.935</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper Limit</td>
<td>182.330</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Fig. 15 Map of change for $\varepsilon=10^{-6}$](image3)

<table>
<thead>
<tr>
<th>Cluster 5</th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
<th>Mean Of The Averages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>177.234</td>
<td>183.992</td>
<td>178.339</td>
<td>182.403</td>
<td>180.492</td>
</tr>
<tr>
<td>Typical Interval</td>
<td>15.219</td>
<td>13.006</td>
<td>15.917</td>
<td>16.558</td>
<td>15.175</td>
</tr>
<tr>
<td>Lower Limit</td>
<td>150.142</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper Limit</td>
<td>210.843</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Fig. 16 Map of change for $\varepsilon=10^{-5}$](image4)
The rates of change varied from 46.81% for $\varepsilon=10^{-8}$ to 80.19% for $\varepsilon=1$. The difference between these rates of change of the two extreme values of $\varepsilon$, is high (33.38%). It was noted that the lower $\varepsilon$ is, the lower the rate of change is as well. These results were compared to real rates of change obtained by applying a standard method of change detection based on differencing (ID).

The results of applying the second advance are depicted in Figure 22. Table 15 gives the rates of change, false change or false alarm and no change.

The results of Table 16 show that applying the standard method of change detection based on differencing gives, on one hand, a rate of change close to that of the first advance when the threshold $\varepsilon=1$. On the other hand, it gives a rate of no change closer to the rate obtained by applying the second advance.

The *a contrario* approach for change detection on high- and low-resolution satellite images allowed several thresholds to be tested according to two methods having a significant difference.

<table>
<thead>
<tr>
<th>Method</th>
<th>Change</th>
<th>No change</th>
<th>False change (false alarm)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>a contrario</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>threshold</td>
<td>47.06%</td>
<td>13.45%</td>
<td>39.49%</td>
</tr>
<tr>
<td>$\varepsilon=\pm 2\sigma$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
IV. DISCUSSIONS AND CONCLUSION

The method of multi-scale analysis developed here has enabled the detection of change whatever the image resolution and number of images tested. Indeed, the points outside the limits calculated for each class will be regarded as changes.

The multi-scale analysis, in case of occurrence of sudden changes, activates an alarm in the event of the advent of any natural phenomenon or the occurrence of a disaster (fires, avalanches, floods ...). In this case, it was shown that there were two points in images I2 and I4 which were outside of the set limits. It was known that these changes correspond to the wetlands and that changes in this area are highly variable.

In addition, changes to the bare soil were able to be located on image I2. As for the other clusters representing vegetation, the green belt, roads and the urban area, no points were found outside of the limits taken into consideration. However, this result does not mean that there no changes occurred in these areas, but indicates that the calculated limits need to be reconsidered.

The advantage of this method is that it can be done with a large number of images with different resolutions, whatever the magnitude of the images.

The disadvantage of this method, however, is that, first of all, it is not quantifiable. Secondly, it is applied cluster by cluster, thereby necessitating classification of the images beforehand, in order to be able to calculate averages, standard deviations and proportion of cluster occupancy.

This work could be improved by exploiting the occupancy rate of the change of clusters and trying to integrate them in the process of detecting multi-scale change.

Global rates of change would be able to be quantified and maps of change could be generated by using the a contrario approach to detect changes.

In addition, it should be noted that the framework proposed clearly improved results compared to the standard approach based on differencing (ID) due to the fact that the method used brought to light the proportion of false alarms.

Indeed, the results of applying the first advance provided rates of change of land uses according to a group of ε-threshold values. Only the exact value of the threshold closest to the reality remains to be defined.

The results of applying the second advance gave rates of change, false changes or false alarms and no change.

Global rates of change could be calculated using change detection based on the a contrario approach. A more detailed study would provide rates of change for each theme. Integration of additional information in the established change detection process would improve the approach.

The results of a contrario change detection proposed by Robin [5] were limited by the fact that objects were only detected if their sub-pixel size was greater than 25% of the LR pixel. In addition, the study proposed by Robin should be compared to real situations on entire image sequences.

REFERENCES

[8] A. andres, "Sur quelques problèmes mathématiques en analyse d’images et vision stéréoscopique", habilitation a dirigé des recherches...


