Urban Growth Analysis Using Multi-Temporal Satellite Images, Non-stationary Decomposition Methods and Stochastic Modeling

Ali Ben Abbes, ImedRiadh Farah, Vincent Barra

***Abstract*—**Remotely sensed data are a significant source for monitoring and updating databases for land use/cover. Nowadays, changes detection of urban area has been a subject of intensive researches. Timely and accurate data on spatio-temporal changes of urban areas are therefore required. The data extracted from multi-temporal satellite images are usually non-stationary. In fact, the changes evolve in time and space. This paper is an attempt to propose a methodology for changes detection in urban area by combining a non-stationary decomposition method and stochastic modeling. We consider as input of our methodology a sequence of satellite images $I_1, I_2, \ldots I_n$ at different periods ($t = 1, 2, ..., n$). Firstly, a preprocessing of multi-temporal satellite images is applied. (e.g. radiometric, atmospheric and geometric). The systematic study of global urban expansion in our methodology can be approached in two ways: The first considers the urban area as one same object as opposed to non-urban areas (e.g. vegetation, bare soil and water). The objective is to extract the urban mask. The second one aims to obtain a more knowledge of urban area, distinguishing different types of tissue within the urban area. In order to validate our approach, we used a database of Tres Cantos-Madrid in Spain, which is derived from Landsat for a period (from January 2004 to July 2013) by collecting two frames per year at a spatial resolution of 25 meters. The obtained results show the effectiveness of our method.

***Keywords*—**Multi-temporal satellite image, urban growth, Non-stationarity, stochastic modeling.

I. Introduction

NOWADAYS, it is widely approved that multi-temporal satellite images are privileged for land-cover monitoring [1], [2]. Moreover, recent trends aim to establish high quality interpretation of the past [3]. Regardless of the methodology, technology and consideration used to extract data form satellite images, remote sensing represents a powerful, dynamic and effective source of data for the land use/land cover changes [2]. Over the last decades, remote sensing technologies have previously shown their importance in monitoring of urban area with different points of view [2], [4]. It represents a key for monitoring rapid urban growth, detecting and measuring a variety of land use/land cover changes.

Generally, works on urban growth modeling have been mostly methodological [5]. Therefore, characterizing the changing trend over time is essential for several environmental applications [1], [5]. Urban growth monitoring presents significant challenges at different scales. The challenges concern not only spatial variability, but also the temporal variability.

In order to provide more accurate monitoring about urban area changes, three issues must be considered: Extracting maximum information from remotely sensed data, quantification of the urban expansion in time (i.e. trend estimation) and location of the expansion according to the spatial scale.

With recent advances in remotely sensed data, several models have been widely used for urban growth monitoring. Based on historical spatio-temporal data, we try to analyse land-use change in urban area. In literature, the commonly used models for modeling land urban growth are: Multi-agent models [6], Logistic Regression [7], Cellular Automata [8], Neural network [9], Hidden Markov model [10], expert system models [11], evolutionary models, hybrid models [12]. Generally, all these methods have been applied without considering a non-stationary data.

The systematic study of global urban expansion using remotely sensed data can be approached in two ways [12], [13]: The first considers the urban area as one same object as opposed to non-urban areas (e.g. vegetation, bare soil and water). The objective is to extract the urban mask. The second one aims to obtain a more knowledge of urban area, distinguishing different types of tissue within the urban area.

The aim of this paper is to investigate the non-stationary character of multi-temporal time series. To overcome this problem, an adaptive decomposition is presented to decompose time series into two components, namely trend and random components.

The outline of this paper is as follows: In Section II, related works of non-stationary decomposition methods are given. Section III describes the proposed methodology for changes detection with non-stationary multi-temporal satellite images. Section IV presents a real case study. At the end, we conclude and draw some future works.

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II. Related Work: Non-Stationary Decomposition Methods

In the literature, several changes detection approaches have been developed [14], [16]. Changes detection is defined as the process of identifying differences in the state of an object or phenomenon by remotely observing it at different times. Changes detection started from approaches using short term SITS, e.g. image differencing, change vector analysis, principal component analysis or tasseled cap transformation-based methods. Unfortunately, they suffer from several profound limitations such as: It has been applied on short time series without noticing the crucial non stationary behavior of the time series, risk of confounding slight natural changes with drastic ones (e.g. considering a temporary conversion of land cover a total transformation of land type), dependence on the image type, time of acquisition, thresholds and control parameters and disregarding the non-stationary data particularity caused by seasonal and trend variations.

Basically, stationarity is defined as a quality of a process in which the statistical parameters (mean and standard deviation) do not change with time [12]. A stationary process, if its first and second moments are never changing in time.

$$E\left(S_t\right) = \mu \tag{1}$$

$$V\left(S_t\right) = \sigma^2 \tag{2}$$

$$\operatorname{cov}\left(S_t, S_{t-h}\right) = f\left(h\right) \tag{3}$$

The first condition states that expectancy is constant over time, thus there is no trend. The second condition states that the variance is constant over time. The last condition designates that the autocovariances only depend on the decomposition in the time.

Statistically, a time series is called non-stationary if the statistical features of the phenomenon are changing over time. Generally, using a non-stationary multi-temporal satellite image in classical land use models produces unreliable and spurious results and leads to poor forecasting and understanding. Land-use changes can be classified in three categories:

- Progressive: This change type could describe a land management or land degradation (e.g. reforestation, deforestation, urbanization, droughts) or due to interannual variability.
- Periodic (i.e. seasonal): In this case, the land cover maintains the same type but not the same behavior or describes a different kind of land cover composition. It could be driven by meteorological factors or human activities.
- Sudden: It is caused by natural hazards (e.g. fires, storms, floods, insects attacks, earthquakes) or human accidents.

Basically, temporal decomposition consists separating a non-stationary time series into three different components, each of which may be related to specific change (e.g. Seasonal, Trend and random). In the literature, several non-stationary decomposition methods have been proposed. Among the different techniques used to monitor changes from multi-temporal satellite image, two groups of classification methods are proposed: Spectral-frequency Researchers using spectral domain try to describe the observations according to the dominant frequency variations, producing a harmonic modeling of the past. The most known approaches are Fourier Transform [11] and Wavelet Transform [13]. In contrast, statistical approaches are based on estimation algorithms. Contrarily to the first group, these approaches are either dedicated to reveal latent components in econometric such as Seasonal Trend Loess or developed especially to reply to remote sensing needs e.g. Breaks For Additive Seasonal and Trend analysis [17], [18] and recently, Detecting Breakpoints and Estimating Segments in Trend analysis [19].

III. Proposed Methodology

A. Overview of the Proposed Methodology

The following section describes the steps involved in this research. As mentioned previously, this study aims to provide a methodology to detect changes in urban area. We consider as input of our methodology a sequence of satellite images I_1, $I_2 \ldots I_n$, at different period ($t = 1, 2, \ldots, n$). Fig. 1 shows the flowchart methodological. Firstly, a preprocessing of multi-temporal satellite images is applied, (e.g. radiometric, atmospheric and geometric). Our methodology incorporates two levels for analysis of urban growth: the first one consists to follow the urban mask over time, which has been already determined by object classification method. It consists of a non-stationary analysis which aims to decompose a time series trend and random variation. The second one aims to establish high quality interpretation on the spatial variability. It includes an unsupervised classification of urban into several land cover type, and the probability of transition between each pair is estimated.

B. Multi-Temporal Satellite Image Classification

The object classification approach aims to define and take into account, in addition to spectral values of pixels, more characteristics of an object, such as proximity, slope, elevation, density of elements. Applied in urban areas this approach allows for example to define a park as an object composed of several land cover types. The object-oriented classification approach is designed to address the problem of heterogeneity of environment.

The high spectral variation in same class and spectral confusion between different land cover classifiers per pixel rendering less effective. Two steps are involved in an object oriented classification are segmentation and classification. Image segmentation blends the pixels in objects.

The attributes used into our classification:

- Spatial Descriptors are defined as the geometry of all sub-objects that compose it. The sub-objects are interconnected by locator operators. (e.g. length, width, area and perimeter).
- Textural Descriptors reveal the macroscopic attributes of objects in an image. It can be used to differentiate between two regions which have a color balance.
- Spectral Descriptors: The radiometry of a semantic object in an image taken by a sensor depends essentially on the composition of the object material.

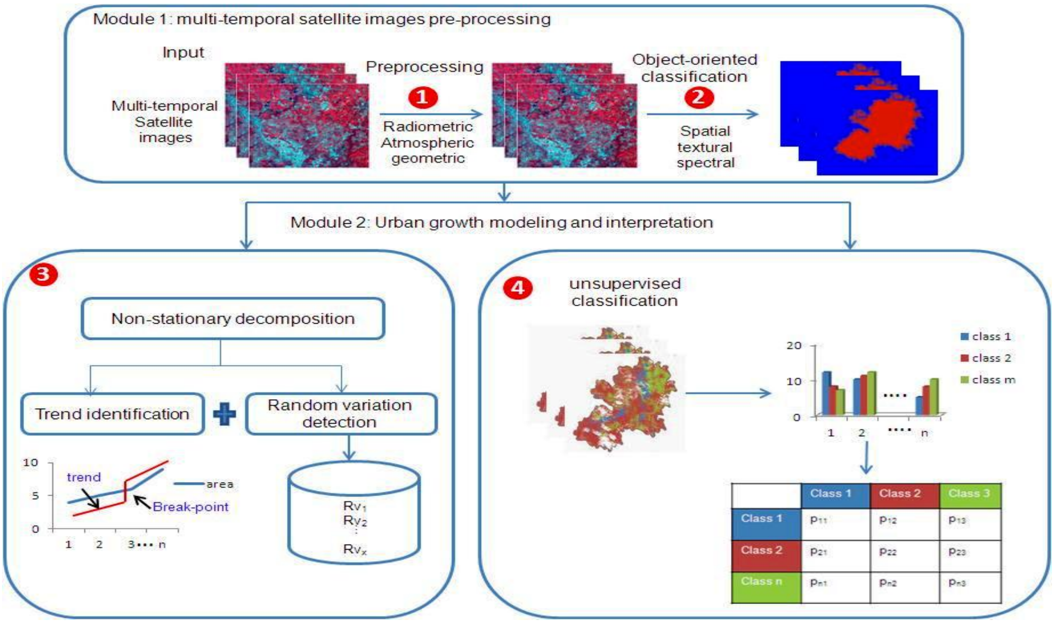

Fig. 1 Flowchart of the proposed methodology

C. Multi-Temporal Satellite Image Classification

The adopted approach in this study is based on the Breaks For Additive Seasonal and Trend analysis (BFAST) [20], [21]. Since their introduction in the literature in 2010, the BFAST has proven to be quite useful in the study of non-stationary processes. BFAST can be used to analyze various types of time series of satellite images and can be applied to other disciplines dealing with seasonal or non-seasonal series time series. BFAST handles only the additive decomposition model (4). For urban area, we are particularly interested of progressive and random changes.

$$S_t = Ct_t + Ca_t \tag{4}$$

where, the trend component is represented by a piecewise linear function which is used to represent both linear and nonlinear variations [16]. It is fixed between the breakpoints $\tau_1^*, \ldots, \tau_m^*$ by:

$$Ct_t = a_i + b_i t \tag{5}$$

where $\left(\tau_{i-1}^* \langle t \le \tau_i^*\right), i = 1, \ldots, m$, *ai* is the intercept and *bi* is the slope of the i^{th} segment. Our aims concern the detecting of random variations and explaining their causes [14]. The random component C_{rt} is defined as the inherent noise [16]. In fact, it is ignored by the researchers. In contrast, it may encompass precious data which is already proved in other fields [21]. Such unexpected values may be observation errors, unlikely events which may occur by chance or special, unlikely events which did not happen by chance. The latter are called random variations in this paper. The detection criterion is based on the hypothesis that the residuals, considered without rare events, are normally distributed. First the value found at the greatest distance of the actual mean is selected as potential rare event. Subsequently we compute the mean and the variance of the remaining residuals. The reduced series is subject to the Jarque-Bera test to examine if it differs significantly from Gaussian noise. These steps are repeated until it statics the null hypothesis [22]. For each random variation detected R_v: $\{R_1, R_2, \ldots, R_n\}$, we select their features (e.g. amplitude and time).

Algorithm 1: Radom variation detection
Inputs : C_{rt}
Outputs: Rv{Rv_1, Rv_2,…Rv_n} avec n=1,2,….n ; Rv_n{Amplitude Rv_n, Date Rv_n}
1 :Repeat
2 : Parameter estimation of N (μ, σ^2) of C_{rt}
3 :If C_{rt} does not follow N (μ, σ^2)
4 : Extract deviants point $R_{vi} \notin$ N (μ, σ^2)
5 : Replace R_{vi} by x ∈ N (μ, σ^2)
6 :Until C_{rt} follows N (μ, σ^2)

D. Intra-Urban Analysis Using Markov Model

This last module of our methodology consists to model the dynamics of land use change in urban area. The main idea is to consider land use change as a Markovian stochastic process. It includes two steps. After classification of land use maps, transition probability matrices for time periods were calculated. An unsupervised classification is an Iterative Self Organizing Data Analysis (ISODATA) algorithm. First of all, ISODATA calculates class means evenly distributed in the data. Secondly, cluster iteratively the remaining pixels [15]. ISODATA is iterative algorithm in that it makes an unsupervised classification. More details of ISODATA algorithm are given in [16]. Before image classification, a classification scheme must be created. In this study, the adopted land use/cover classification scheme included four land use classes as mentioned in Table I. Furthermore, the Markov chains have been widely used for land-use modeling. The Markov chain gives a simple model by which a dynamic land use could be established and examined. In addition to quantifying the changes that happened. Markov property considers the probability of moving to next state depends only on the present state and not on the previous states:

$$\Pr(X_{n+1} = x \mid X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = \Pr(X_{n+1} = x \mid X_n = x_n)$$

TABLE I
CLASSIFICATION SCHEME USED IN THIS STUDY

	Cover type	Description
1	Dense built-up	Highly clustered buildings
2	Less dense built-up	Slightly separate buildings
3	Vegetation	Composed of trees and shrubs
4	Bare soil	Non-built-up areas and open without vegetation

The primary assumption is to consider land use change as a stochastic process as well as the different land cover types are the states of a chain. That characterize the likelihood that one state (e.g., vegetation) changes to another state (e.g., Dense Built-up) within a specific time period. In our context, a transition matrix contains the probability corresponds to change between land-cover class i fromanother class j during a time period. p_{ij} was determined over a specific period from time $t-1$ to time t. A transitionmatrix contains the number of pixels that are expected tochange to a land-use class from another class during a time period. The Markov transition probability P over specific period was determined as:

$$\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}, \sum_{i=1}^{n} p_{ij} = 1 \text{ and } 0 \le p_{ij} \le 1, (i, j = 1, 2, \ldots n) \tag{6}$$

IV. EXPERIMENTS AND RESULTS

The purpose of present paper is to analyze land use changes in Tres Cantos-Madrid from 2004 to 2013.

A. Study Area and Data

Tres Cantos is a township located in the autonomous community of Madrid (Fig. 2). It is the youngest incorporated municipality in Spain, situated 22 km at the North of the capital. Landsat images from 2004 to 2013 (two images for each year) were used in this research (Fig. 3). Due of their spectral, spatial, and temporal resolutions. Landsat images among the widely used satellite for mapping and analyzing land use/land cover. The time sampling is six months (January-July). All images were geometrically registered according to the UTM system (WGS 84). The images set used in this experiment were collected from (http://glovis.usgs.gov). The following figures respectively illustrate this image time series.

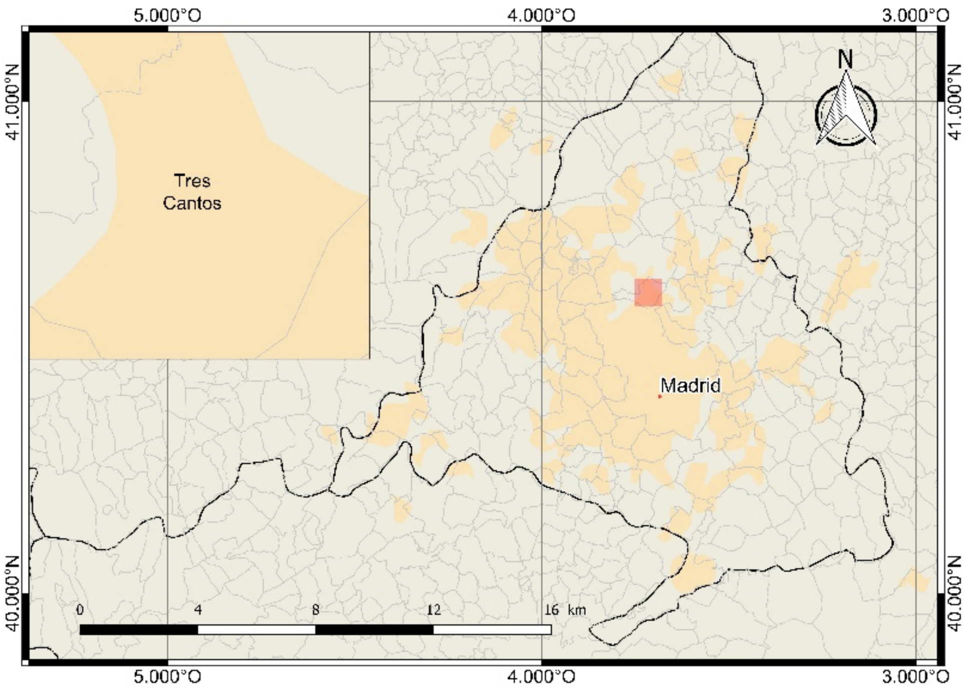

Fig. 2 Studied area location

B. Pre-Processing

Landsat image contains seven band. Each band represent an electromagnetic spectrum. For urban study with Landsat image we should use the color composite (RGB). The color composition associates a satellite image to the primary colors (RGB). Consist to combining in a single image of near infrared, visible and green visible bands.

TABLE II
RANDOM VARIATION

Random variation	Date	Amplitude
1	January 2007	+19.35%
2	July 2007	+8.77%
3	July 2007	+4.32%
4	January 2013	+4.77%

C. Results

Fig. 3 shows the object classification result; each image contains the urban are and non urban area. Fig. 4 shows the object classification result, each image contains the urban area and non-urban area. In 2004, the total investigated area was determined by 700 km^2. During 2004-2013 the urban evolved with a percentage of 51% as shown in Fig. 5. From this image, it is clear that there has been a significant change (51% of the total area) during the 10-year period. In the study, there are four cases (as shown in Fig. 3) for random change, since the evolution of normal urban is in the range [0.10% -3.24%]. In July 2007, the urban growth is 19.35% that caused by an important demographic pressure (+12%) that began in 2004. Fig. 7 shows the land use change from 2004 to 2013.We have selected 200 reference locations in the study area, which, allows determining the land use type. Subsequently, it has been verified with Google Earth. The overall classification accuracy and the kappa statistics for the classified images is comprised between 0.84 to 0.86, and respectively urban or dense built-up land and less dense built-up have increased in area (by 50% and 24% respectively), and vegetation has decreased in area (by 43%).

Land use maps were produced for the study period using the ISODATA as given in Fig. 5. Dense built up area covered 700 km^2 and vegetation land covered 3 km^2, while the bare soil covered 610 km^2. During the studied period, built up area has been mounted 50.12% and vegetation has been lost 24%. In the period from 2004 to 2013, the areas of vegetation in Tres Cantos decreased substantially, whereas the areas of built-up and bare land soil increased.

In the period 2004-2013, the areas of vegetation and bare soil land in Tres Cantos decreased substantially, whereas the areas of built-up land increased. During the studied period, built up area has been gained 50.12% and vegetation has been lost 24%. The transition probability matrix was calculated using Markov chain analysis for the time period of 2004-2013 as shown in Table III.

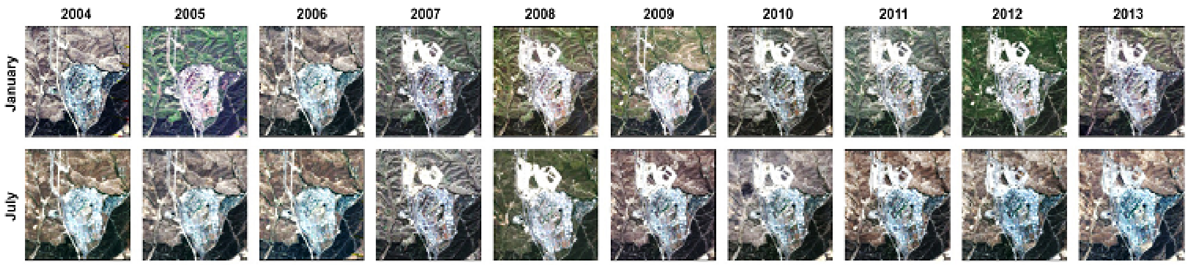

Fig. 3 Landsat time series images from 2004 to 2013

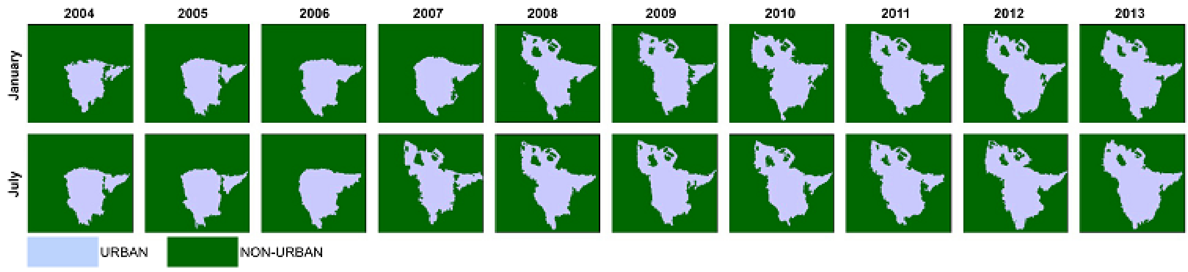

Fig. 4 Obtained classification

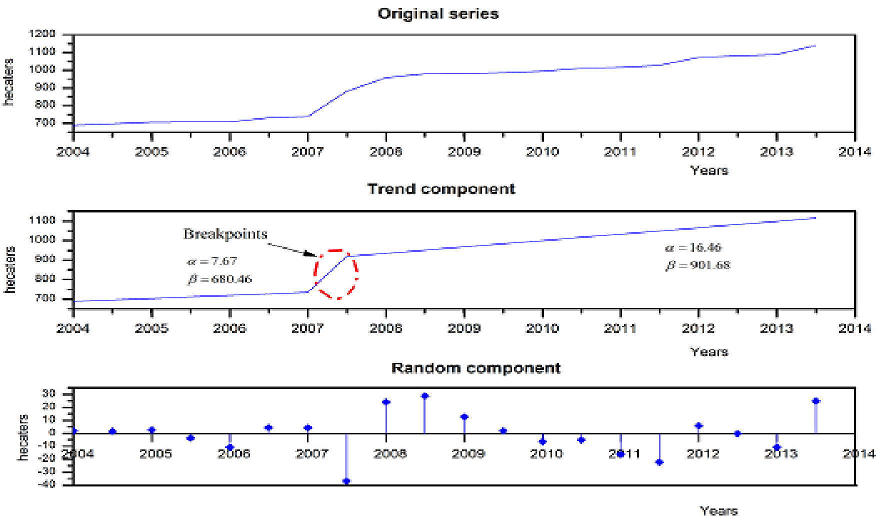

Fig. 5 Decomposition time series

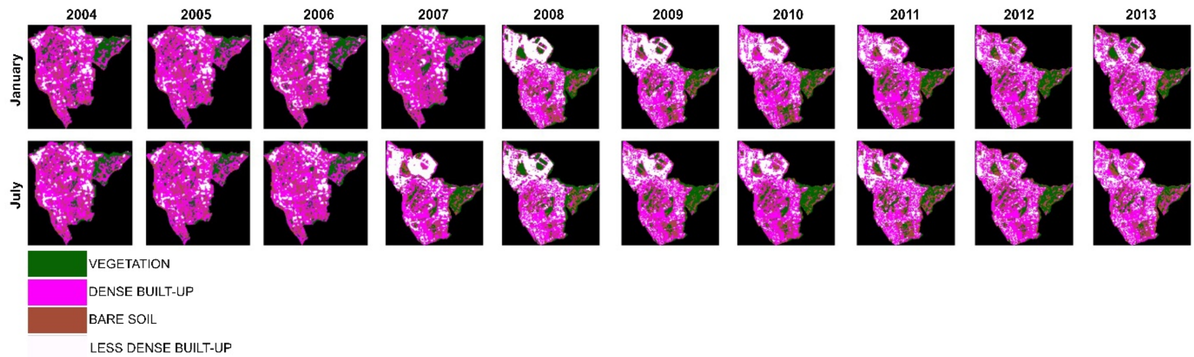

Fig. 6 Intra-urban classification using ISODATA

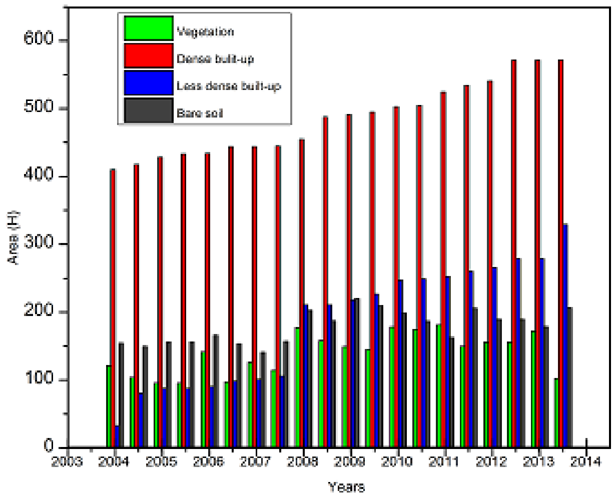

Fig. 7 Changes of land use

TABLE III
TRANSITION PROBABILITY MATRIX CALCULATED USING LAND-USE MAPS 2004 AND 2013

Land use classes	Dense Build-up	Less Dense build-up	Vegetation	Bare soil
Dense Build-up	0.98	0.2	0	0
Less Dense build-up	0.6	0.3	0	0.1
Vegetation	0.3	0.2	0.4	0.1
Bare soil	0.1	0.3	0.2	0.4

V. CONCLUSION

In this paper, we have presented a methodology for detection changes aspect in urban areas which take into account non-stationary data. We have considered the multi-temporal satellite images as information source, which are applied for a specified treatment in urban extraction. We have also proposed an adaptive multiplicative decomposition to have two parts: The first consists of trend that depends on the period. The second consists of the random variations. The evaluation of robustness and fidelity of our model provides satisfactory results that encourage us to study other perspectives such us modeling the random component in an intelligent way, integrating the presented methodology in a predictive model and studying nonstationary in intra-urban.

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