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MODELS FOR MONITORING THE DETECTION OF LAND USE CHANGE THROUGH THE CLASSIFICATION OF URBAN AREAS

MODELE DLA MONITOROWANIA WYKRYWANIA ZMIAN UŻYTKOWNIA TERENU PRZEZ KLASYFIKACJĘ OBSZARÓW ZABUDOWANYCH

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Introduction

Remote sensing in urban areas has been a challenge for quite some time, due to their complexity and fragmentation with the combination of man-made and natural features. High-resolution satellite images offer potential for feature extraction and spatial modelling of urban areas. Land use classification of urban areas may become possible by exploiting current high-resolution sensor data. This proposed approach incorporates spectral information from multi-spectral Spot images in an hierarchical image segmentation based on semantically meaningful thresholds. Urban areas are divided into various structure densities depending upon land occupation and pixel neighbours, each region relating an administrative area, already converted (each pixel), to Points Of Interest (POIs) to form a geographic database for our study in the income sections. The first stage, based on the identification of groups of points, exploits the fact that POIs are geographically distributed in clusters. In highly urban regions, the spatial density of the POIs is high, while in sparsely populated areas the density of points is much lower. To identify these different regions, a spatial density-based clustering technique was adopted. Once the groups of points are identified, the calculation of the boundaries of the areas containing each group of points defines the new regions. The third stage is where the regions are classified. This research is intended to find a way to delineate areas of different land use and identify the land use type in every delineated area. Delaunay triangulation is deployed to create spatial associations and structural analysis toward the spatial clustering of physical features in image space, with the aim of identifying land use. Delaunay triangulation has been widely used in spatial analysis and spatial modelling (Bundy, Furse, 1995). We use Delaunay triangulation for deriving spatial relations between image objects and for structural analysis; mathematical morphology is applied to find the solid core of a spatial unit in 2D space; a Kernel Density function used to calculate a magnitude per cluster area from the centroid point features using a kernel function to fit a smoothly tapered surface to each point. The Voronoi algorithm is proposed for deriving explicit boundaries between spatially adjacent land-use units. To test the approach, we selected a site in a suburban area within Barcelona Municipality, Spain.

Spatial Clustering of Pixels Based on Shortest Links between Adjacent Urban Objects

Delaunay triangulation applied to a raster image of a land-cover type (e.g. urban areas) is a good tool for finding adjacent areas and the shortest distance between them. To do so, we must eliminate triangle edges that link two pixels comprising the same object. The remaining edges indicate adjacent objects. Thus the shortest edge between two adjacent objects can be extracted to measure how close these objects are situated (i.e. their proximity). We describe how a set of geographic data can be used to create a space model based on location contexts. The proposed process includes three major stages and is illustrated in Figure 1.

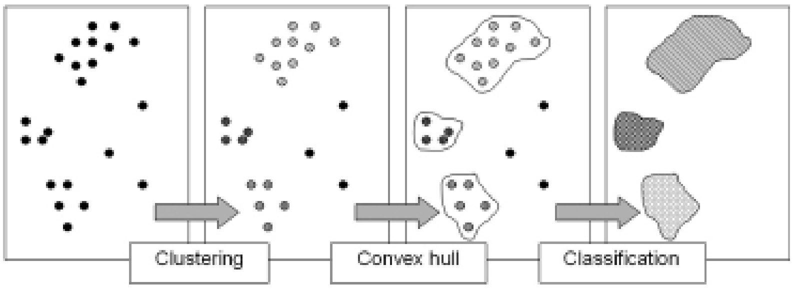

Figure 1. Generating location contexts from POIs

Spatial Analysis Using Delaunay Triangulation

The Delaunay triangulation links up the natural neighbours into a point set by triangle edges; the edges of such triangles indicate the proximity relationship between the linked points. If applied to the centres of pixels that represent image objects, we get triangle edges between adjacent pixels comprising the same image object and triangle edges that link up two pixels of adjacent image objects, the two pixels satisfying the natural neighbour criterion. Thus the shortest links between two adjacent image objects can be derived from the length of the edges that link two adjacent image objects. In raster to vector conversion of the labelled image, the centre of a building pixel becomes a point; we use the coordinates (x, y) of a pixel to represent a point vector, as shown in Figure 2, and invent the ID of the point. To extract adjacent image objects, we deploy Delaunay triangulation for all pixels that constitute image objects such as buildings; each triangle edge indicates proximal points (pixels), as shown in Figure 3.

POIs and morphological image processing

Classification of land use datasets normally carries a lot of noise (seed pixels) which makes it difficult to analyse and understand the conjunction and the similarity of zones for urban growth study; morphological image processing will simplify and identify the urban form. Since the spatial presentation of an image object in image space is a binary segment, the region adjacency graph (RAG) can be created using morphological image analysis.

The morphological approach is based on operators such as dilation, erosion, opening, closing etc. Dilation can be used to determine how close adjacent objects are by controlling the repeated application of the dilation operator till various segments merge into one. Clustering is one of the most important morphological analysis tasks. The goal is to divide a collection of objects into groups, such that the similarity between objects in the same group is high and objects from different groups are dissimilar. The natural clusters extracted by this approach are presented in Figure 5. In this experiment, the image cluster of urban areas were combined in a single image (see Figure 4); a convex hull is applied to the cluster areas to obtain homogeneous zones (see Figure 6). Centroid point patterns of clustered satellite images from 1986 to 2004 (see Figure 7) were examined to determine whether the urban pattern of Barcelona, within and beyond the municiple boundary, fits into one of the broad classifications of random, uniform or clustered.

Monitoring Sprawl using Smoothing Parameter and Kernel Density

This section will concentrate on the analytical process in relation to centroid point data distributions. Point pattern events on maps change through time, so an important aspect stressed by many authors (Zeng, Chen, 2006) (Diggle, Chetwynd, 1991) is to try to make the linkage between the spatial map and temporal changes. Figure 8 shows the centroids of joined clustered areas in Barcelona municipality over the period 1986-04. Visual inspection suggests that several clusters of different types and sizes exist, but the initial inspection of the mapped data is somewhat misleading. Examining the source dataset shows that most of the point dataset consists of closest locations, i.e. points represent a closest isolated urban fabric.

Assuming the point set is un-weighted, and exhibits marked clustering, it is then useful to identify factors such as: (1) where are the main (most intensive) clusters located? (2) Are clusters distinct or do they merge into one another? (3) Are clusters associated with some known background variable, such as reflecting variations in land-use (farmland, forest, water etc.)? (4) Is there a common size to clusters or are they variable in size? (5) Do clusters themselves cluster into higher order groupings? (6) If comparable data are mapped over time, do the clusters remain stable or do they move and/or disappear? Again, there are many questions and many more approaches to addressing such questions.

An alternative approach to density computation for two-dimensional point-sets is based on one-dimensional (univariate) statistical analysis. The usual way in which we examine patterns in the centroide dataset is by smoothing the data to iron out the connectivity that takes place from data that originally represented urban clusters. The simplest way is to take a moving average of the data, which consists of averaging the data in a window or neighbourhood defined around each basic location. A more controlled method for achieving such smoothing is by using a kernel density estimator (KDE) such as the one in the proprietary GIS software ArcView (Mitchell, 1999). This is based on Silverman's (Silverman, 1986) Quadratic and it is used to generate different levels of surface smoothing choosing different sizes of bandwidth – akin to different window sizes. With a specific kernel function, it is the value of the bandwidth which determines the degree of averaging in the estimate of the density function. The possibility of "manipulating" the results of the KDE through the application of different bandwidths and functions can be empirically translated into testing different assumptions about the spatial behaviour of a particular variable, such as its distance decay effects. In Figure 9 the kernel density procedure has been applied to a dataset of the cluster centroids of Barcelona Municipality. Cases are shown as points in this map, with areas of higher-kernel density being shown in darker tones. The highlighted areas in the upper left of the map represent lower-kernel density.

Urban Change Detection Using Dynamic Voronoi Data Structure

Static point Voronoi tessellations are common in the literature, and algorithms have been used for many years. Less well known are dynamic algorithms that allow point creation, deletion and movement, and also Voronoi tessellations of more complex objects – typically line segments as well as points (Aurenhammer, 1991). Algorithms for generating the simple point Voronoi tessellation have improved significantly in theoretical efficiency in recent years. However, as a major motivation for this work concerned the maintaining of a map when urban cluster centroids (see Figure 8) are moving over time, an alternative technique was developed that maintained the Voronoi spatial relationships while map objects were being inserted, deleted, or displaced. This is achieved by determining when the Voronoi cell of a moving point gains or loses a neighbouring cell, moving the point to that location, and locally updating the topological structure accordingly.

Dynamic Voronoi and Interpolation Cluster Centroid Data

The natural neighbour (Sibson, 1981) (Watson, 1987) method of interpolation is based on the idea that if the "query point" (at the location where it is desired to make an interpolation estimate- i.e. new centroid of a new urban cluster area) is inserted into the Voronoi tessellation formed by the real data points, then it will reduce ("steal") some area from the adjacent Voronoi cells. These areas are ideally suited as weights to be used for calculating the weighted average of the weights of the neighbouring data points. When the query point coincides with a data point all of the "stolen" area will be taken from that particular data point's Voronoi cell.

This produces one of the few spatial models that can guarantee that an interpolated surface both passes through all data points and has no discontinuities or other artefacts. Figure 10 shows that the interpolated surface resulting from this is continuous within the convex hull of the data, the red colour represents the smallest Voronoi cell (spars built-up areas) and the green colour present the biggest Voronoi cell (high or no built-up area), time and urban growth will help each cell to be divided (new built-up areas) into two or more smaller cells, when the cell areas become zero, the conjunction neighbours will explode to become again one big Voronoi cell illustrating high built-up area.

Calculating the Nearest Neighbour Distance Statistics

The Average Nearest Neighbour Distance tool measures the distance between each feature centroid and its nearest neighbour's centroid location. It then averages all these nearest neighbour distances. If the average distance is less than the average for a hypothetical random distribution, the distribution of the features being analysed are considered clustered. If the average distance is greater than a hypothetical random distribution, the features are considered dispersed. The index is expressed as the ratio of the observed distance divided by the expected distance (expected distance is based on a hypothetical random distribution with the same number of features covering the same total area).

The Nearest Neighbour Distance index can give us an idea whether or not we're dealing with clustered or dispersed data, as it measures the average distance between points in our data and compares the measurement to the expected measurement (a hypothetical random distribution). The Nearest Neighbour Distance index can essentially be represented as:

— (<1-clustered) — (1-random) — (>1-dispersed) —-

Scores less than one indicate clustering, and scores higher than one indicate dispersion. The results of running the tool on our Voronoi datasets are illustrated in Figure 11.

Conclusion

The experimental results show that the proposed pixel-based approach is powerful for spatial clustering. Delaunay triangulation is a good tool for extracting proximity relations among disjoint objects, such as urban areas. The shortest links between objects based on Delaunay triangulation allow us to identify natural clusters. The natural clusters consist of urban areas that are identified by the nearest neighbours. The natural clusters represent the elementary clusters of possibly larger clusters that represent land-use units. Whether adjacent natural clusters should be combined is decided from the shortest edges (Delaunay triangulation) that link the natural clusters and by checking the edge length (the shortest distance between clusters). The experimental results and acquired relationships show that the shortest distance between clusters and similarity measures in terms of residential segments are good measures.

This paper approaches the measurement of municipal urban change from a strictly morphological perspective, drawing upon previous experimental analysis of satellite images dating from 1986 to 2004, in order to quantify and analyse the process of 'periurbanisation' which has been experienced in Barcelona over this period. At the same time, the popularity of the kernel density estimation (KDE) approach is examined to determine the highest densities form centroid cluster point 'hot spots' to illustrate urban change detection. Centroid point patterns usig a Voronoi diagram are also examined to understand urban pattern behaviour, which is usually broadly classified as random, uniform or clustered, both within the confines and beyond the edges of Barcelona's municipal limits.

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Streszczenie

Na przestrzeni ostatnich kilku dekad zaobserwować można występowanie niekontrolowanego, nieskoordynowanego i nieplanowanego rozwoju urbanizacyjnego, powodującego rozprzestrzenianie się miast w wielu częściach globu. Gwałtowność dynamiki urbanizacyjnej ma znaczący wpływ na układy przestrzenne związane z rozwojem i ekspansją wielkomiejskich obszarów. Hiszpania, w której teren podlega urbanizacji w o wiele wyższym stopniu, niż wynikałoby to ze wzrostu populacji, nie stanowi wyjątku. Znaczna część ekspansji obszarów (pod)miejskich odbywa się kosztem gospodarstw rolnych, lasów oraz innych obszarów otwartych i zazwyczaj jest wynikiem niskiego zaludnienia tych obszarów. Rozsądne planowanie użytkowania terenu oraz zachowanie otwartej przestrzeni są w Hiszpanii ważnymi problemami, jednakże obecnie dostępne informacje na temat rozprzestrzeniania się miast i zmian użytkowania ziemi są bardzo niewielkie. Niniejszy artykuł przybliża kwestie pomiaru zmian miejskich obszarów zabudowanych z perspektywy czysto morfologicznej, oparte na poprzednich eksperymentalnych analizach obrazów satelitarnych datowanych na lata 1986–2004, pokazujących, że podejście pikselowe jest skuteczne dla grupowania przestrzennego, celem kwantyfikacji i analizy procesu „peri-urbanizacji", co było celem doświadczenia w Barcelonie na przestrzeni tego okresu. Równolegle sprawdzana jest przydatność podejścia estymacji gęstości jądra (KDE) celem określenia najwyższej gęstości na podstawie „obszarów hot spot" centroidów klastrów, by zilustrować wykrywanie zmian obszarów zabudowanych. Poprzez diagram Voronoi'a sprawdzono również układy centroidów w celu zrozumienia zachowania układu obszarów zabudowanych, które zwykle jest szeroko klasyfikowane jako losowe, jednorodne lub zgrupowane, zarówno w ramach oficjalnych granic miejskich Barcelony, jak i poza nimi. Niniejsze badanie podzielić można na podstawowe etapy:

- *wyodrębnienie rozłącznych obiektów z klasyfikacji użytkowania terenu na podstawie triangulacji Delone'a,*
- *monitorowanie nielicznych zmian obszarów zabudowanych przy użyciu parametru wygładzającego oraz gęstości jądra,*
- *wykrywanie zmian obszarów zabudowanych przy użyciu dynamicznej struktury danych Voronoi'a,*
- *obliczenie statystyki odległości najbliższego sąsiada oraz dokładności.*

Na koniec warto nadmienić, iż zaprezentowane podejście można wykorzystać do monitorowania zmian różnego rodzaju klas użytkowania ziemi na podstawie klasyfikacyjnych zbiorów danych.

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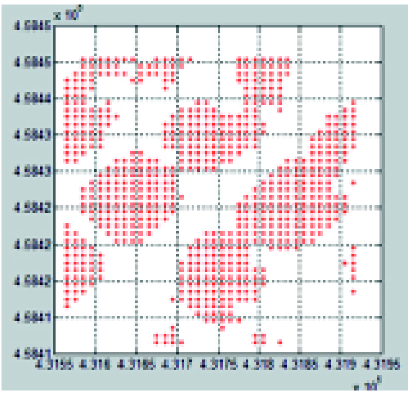

Figure 2. Pixels (points) embedded by image objects such as buildings, Barcelona city, 2004

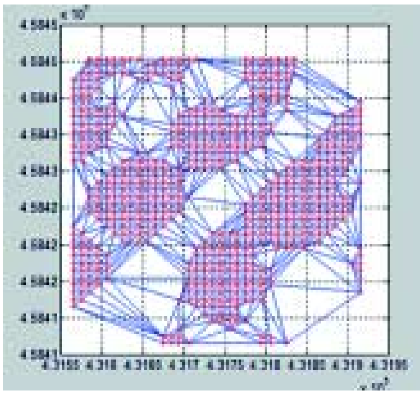

Figure 3. Delaunay triangulation deployed in all building pixels

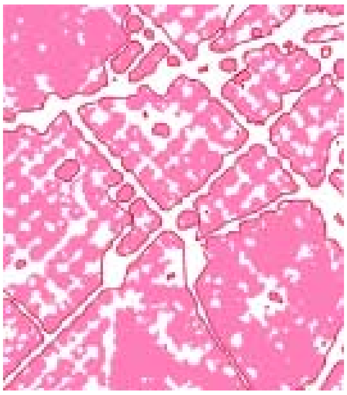

Figure 4. Combined image using image segments of urban areas

Figure 5. Extracted spatial units based on morphological analysis, a raster presentation of clustered blocks in Barcelona city

Figure 6. Reform urban clusters areas using Covex hull algorithm

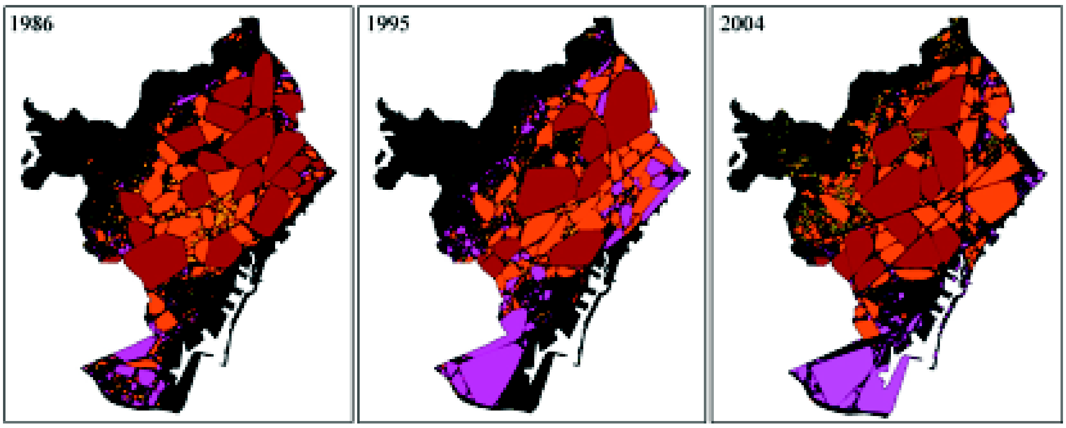

Figure 7. Multi-temporal clustered classification results, Barcelona municipality

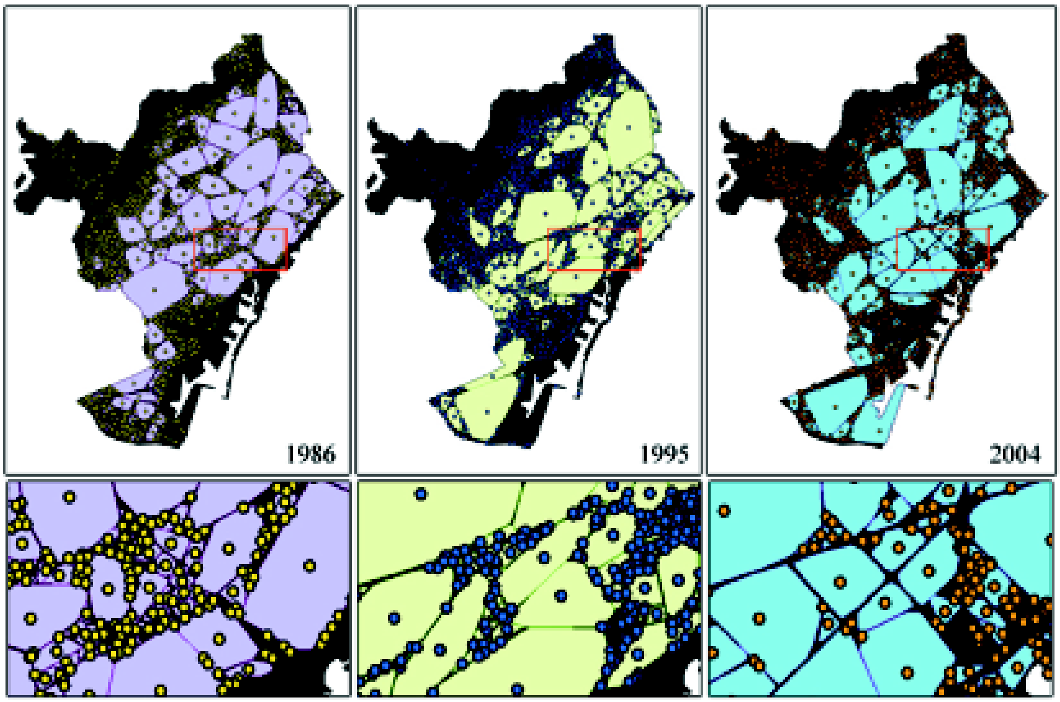

Figure 8. Centroid point dataset corresponding to multi-temporal joined cluster areas

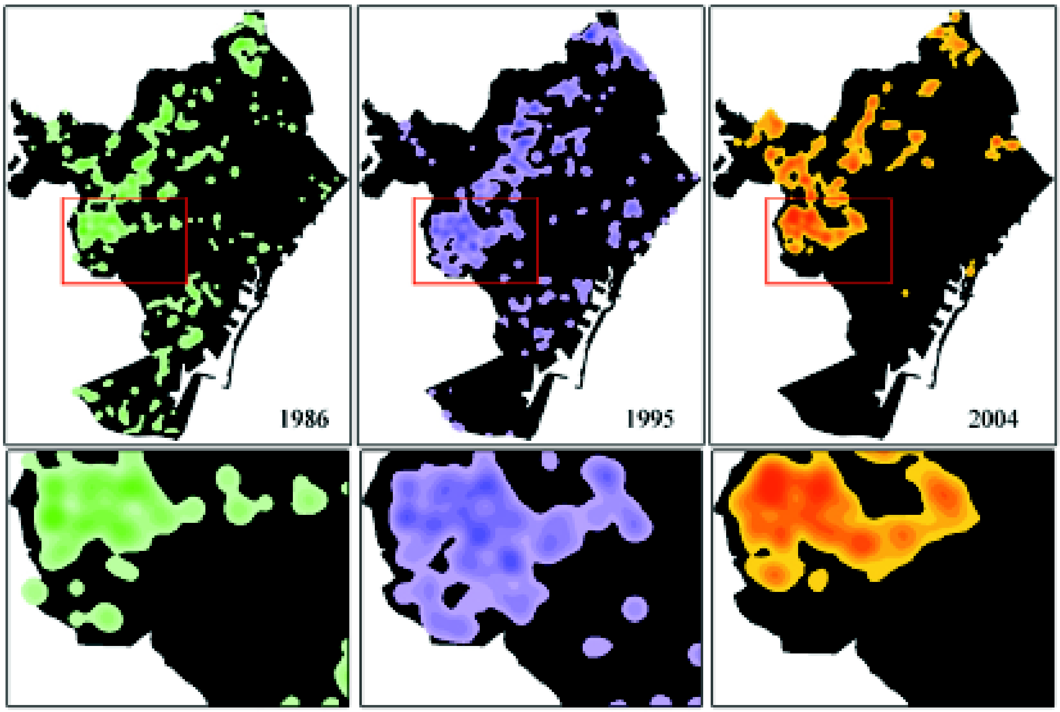

Figure 9. Change of the smoothing parameters of Urban Density. Kernel density with window 10 by 10 metres and 300 m search radius already applied for above results

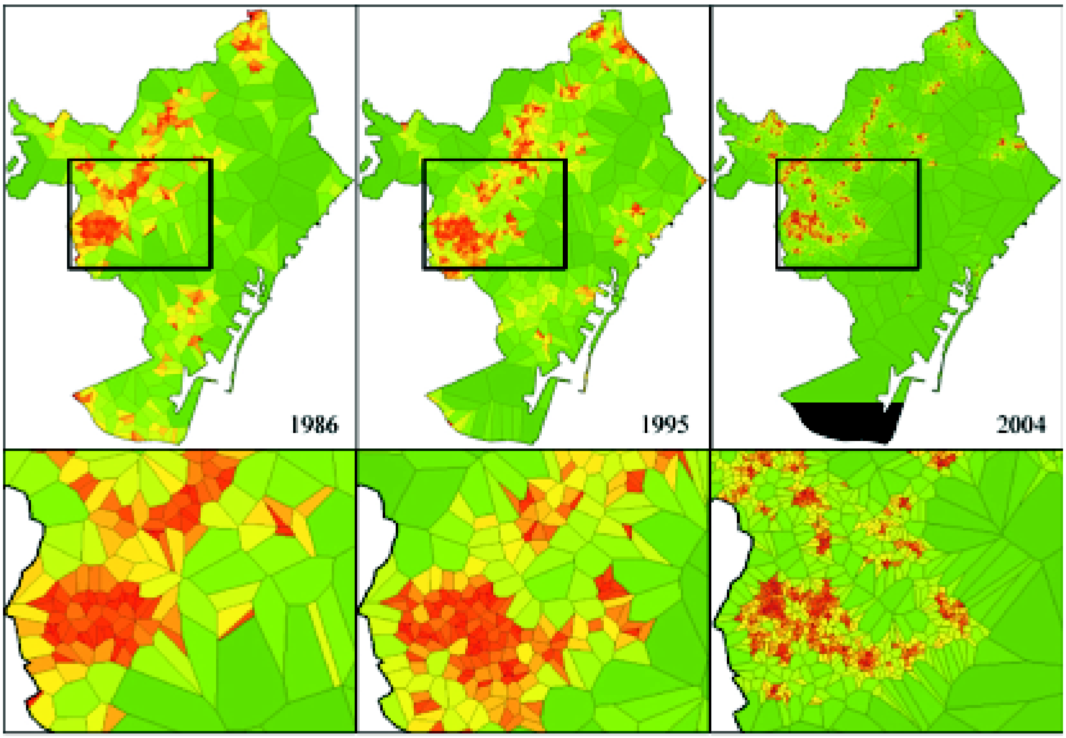

Figure 10. Dynamic Voronoi for multi-temporal map illustrates change detection presented by moving cluster centroid from Voronoi cells

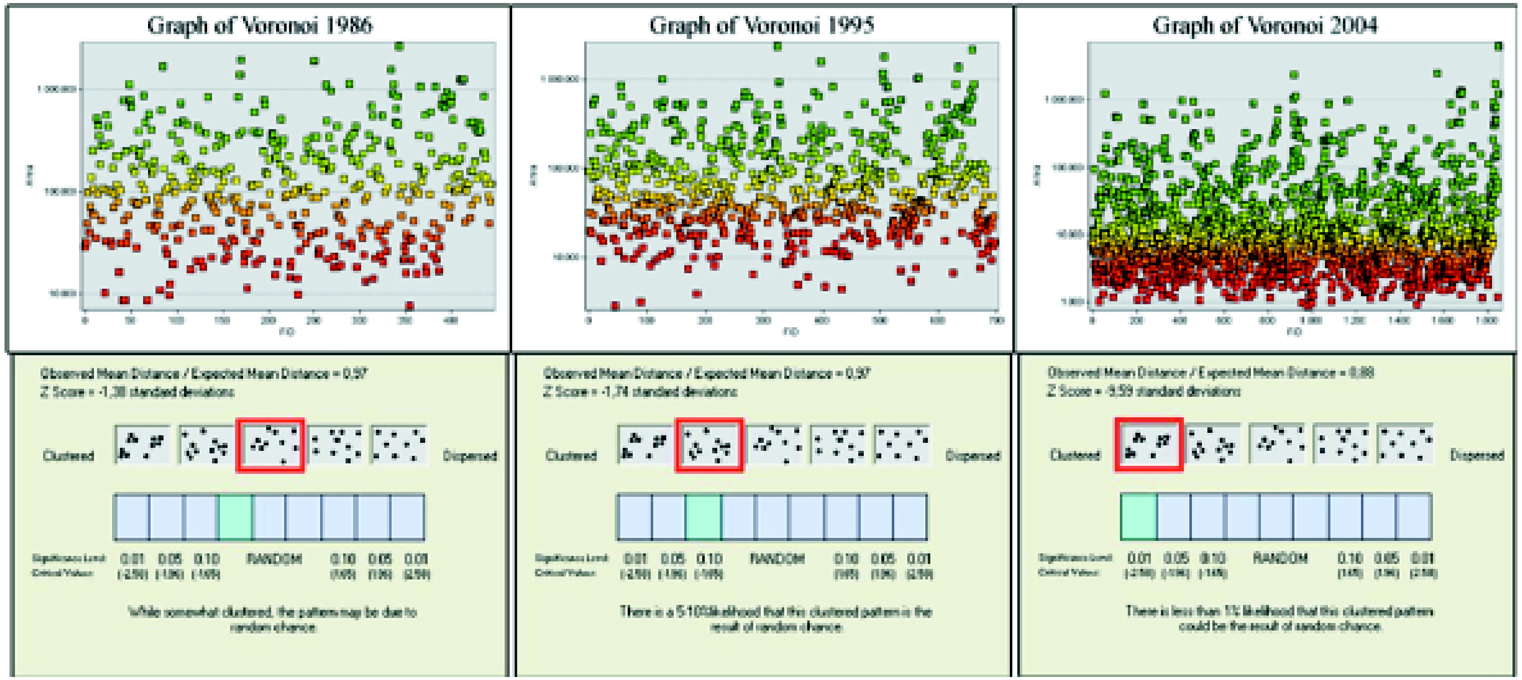

Figure 11. Voronoi nearest neighbor index expressed the ratio of the observed distance divided by the expected distance