Impact of user-settings on land cover change estimation

(Assessing a prototype land cover change mapping method)

Mina Naeimi
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Impact of user-settings on land cover change estimation (Assessing a prototype land cover change mapping method)

by

Mina Naeimi

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Thesis Assessment Board

Chairman: Prof. Dr. Ing. W. (Wouter) Verhoef
External Examiner: Dr. Z. (Zoltan) Vekerdy
First Supervisor: Dr. Ir. C.A.J.M. (Kees) de Bie
Second Supervisor: Drs. R.G. (Raymond) Nijmeijer

UNIVERSITY OF TWENTE.

ITC FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

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Dedicated to my parents

Firouz and Shookooh

Abstract

Land cover change is an important environmental issue which impacts on ecosystem conditions. Thus, it is very crucial to monitor on-going changes and to predict future changes. In recent years, several time-series-based methods have been proposed in the context of multi-temporal imagery analysis. The prototype change detection method assessed in this study uses long term hyper-temporal imagery and is able to generate continuous representations of on-going land cover changes. The prototype method calculates land cover changes based on two preliminary user-settings: 1) “period within the year” and 2) “threshold” (pooled standard deviation (SD) values). This study focused on the impacts that different choices of these user-settings have on the accuracy of generated land cover change maps through the prototype method. SPOT 10-day MVC NDVI images with 1 km^2 resolution from 2000 to 2004 as “reference period” and 2009 as “cover change assessment period” were used to generate land cover change maps using different user-settings of the prototype method. Orthophotos of 2004 and 2008/2009 and field data collected of 2011 in Andalucía, Spain; where the study was conducted; were used to calculate observed changes between 2004 and 2008/2009. The analysis was carried out for 28 pixels of 1 km^2 representing both natural and semi-natural land cover. This study successfully indicated the importance of the user-settings for the prototype method and emphasized that different choice of the user-settings have influence on generated land cover change maps. The study showed that the choice of “1.5” for “threshold” and “whole year” for “period within the year” with 85% agreement between simulated changes and observed changes are the best choices of user-settings for the Andalucía region. The study showed an over-estimation of observed changes when “threshold” was equal to “1.0” whilst an under-estimation of observed changes was seen when the threshold was higher than “1.5”. The results verified that the prototype method using the chosen user-setting performed accurately in the area having natural and semi-natural land cover in Andalucía, but to find the best choice of user-settings for other areas the prototype method needs to be calibrated.

Keywords: Land cover; Change detection; Hyper-temporal; User-settings impact; Accuracy assessment

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1. Introduction

1.1 Background and significance

Land cover is a discrete term which refers to the physical surface of the earth including natural and cultivated vegetation and man-made features (Gomarasca, 2009). Different factors such as environmental, social, economic and even political factors influence and change land cover regionally or even globally over time (Ellis, 2010). Changes in land cover can be related to "natural dynamics (vegetation succession, intra or inter annual variability)" or to "human activities" (Bontemps *et al.*, 2008) for instance due to fire, deforestation, and agricultural or urban expansion. Land cover changes have a significant impact on ecosystem conditions (hydrology, climate changes and biogeochemical cycles) and create environmental issues (Bontemps*, et al.*, 2008; Skole *et al.*, 1997). Information about land cover change is very essential in natural resource management (Boles *et al.*, 2004).

Land cover changes are categorized in two categories, 'land cover conversion' and 'land cover modification' (Coppin *et al.*, 2004b). The first category reflects a complete land cover change, i.e. from one major land cover class to another, the second category reflects subtle land cover changes within a given major land cover class (Coppin*, et al.*, 2004b).

Land cover change detection is the process of identifying differences in the state of land cover by observing it at different time (Singh, 1989). The use of satellite imagery to detect land cover changes has drastically grown since 1972 (Lunneta, 1999). In recent years the availability of satellite imagery makes it possible to detect land cover changes at global, regional and local scales through multi-temporal analysis concerning the fact that land cover varies over time. Monitoring land cover changes through time-series analysis of e.g. hyper-temporal imagery, provide more essential information especially in areas where land cover rapidly changes (de Bie *et al.*, 2008; Nguyen *et al.*, 2012). Also, hyper-temporal images provide the potential for higher accuracy in mapping different land cover classes (Khan *et al.*, 2010; Nguyen*, et al.*, 2012). SPOT-VGT, MODIS-Terra and NOAA-AVHRR sensors capture required data for hyper-temporal analysis.

Introduction

The term of vegetation indices describes the relation between satellite data and crop characteristics. It provides information about condition of vegetation. Since vegetation index reflects the phenological patterns of vegetation, they are widely used for monitoring and detecting land cover changes (Archer, 2004; Davenport *et al.*, 1993; de Bie, *et al.*, 2008; Khan, *et al.*, 2010; Lunetta *et al.*, 2006; Lyon *et al.*, 1998). One of the advantages of vegetation index is that atmospheric effects such as effect of clouds are reduced (Doraiswamy *et al.*, 2007). The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index to monitor land cover (de Bie, *et al.*, 2008; Townshend *et al.*, 1986; Ünsalan *et al.*, 2011); it can be easily derived from remote sensing imagery such SPOT-VGT, MODIS and NOAA-AVHHR data by dividing the difference between near infra-red and red reflectance measurements by their sum (Goward *et al.*, 1991; Tucker, 1979). NDVI can provide information about land vegetation type (Knight *et al.*, 2006).

Many methods have been proposed to detect land cover changes using satellite images. A variety of these methods have been reviewed by Singh (1989), Jensen (1996), Lunneta (1999), Coppin, *et al.* (2004b), Lu *et al.(2004)*. Singh (1989) discusses various methods such as Principal Component Analysis (PCA), Univariate image differencing, Vegetation index differencing, Image rationing, Image regressions, Change Vector Analysis (CVA), Post classification comparison and direct multi date comparison. Lunneta (1999) and Coppin, *et al.(2004b)* classified the change detection methods to pre-classification and post-classification. Also, Coppin, *et al.*(2004b) categorized change detection methods in two categories based on the temporal characteristics: “bi-temporal” and “temporal trajectory” analyses. “bi-temporal” methods assess change detection between two dates. ‘Time trajectories’ or ‘Time profiles’ methods assess the change detection on time-profile based data with multi-time scale. Also, the time-series analysis makes it possible to characterize vegetation dynamics on different temporal scales to differentiate between gradual or rapid changes (Lambin *et al.*, 2006).

The majority of the change detection methods discussed above are based on limited time imagery and they compare single-date or multiple dates with irregular frequency based on aspects of land surface (Allen *et al.*, 2000; Cohen *et al.*, 1998; Coppin, *et al.*, 2004b; Feng *et al.*, 2011; Lu, *et al.*, 2004; Muchoney *et al.*, 1994; Zhou *et al.*, 2008). In the past few years, interest in the development of change detection technique through time-series analysis is growing and several time-series methods have been proposed in the context of multi-temporal analysis but with no high image frequency such as

Principal Component analysis (Young *et al.*, 2001), Change vector analysis (CVA) (Bayarjargal *et al.*, 2006; Lu, *et al.*, 2004), Univariate image differencing (Ingram *et al.*, 2005; Muchoney, *et al.*, 1994), Image regressions (Fraser *et al.*, 2005), trajectory-based change detection (Kennedy *et al.*, 2007) and object oriented methods (Conchedda *et al.*, 2008; Desclée *et al.*, 2006) are based on multi-temporal analysis. There are only a few methods which have solutions for monitoring and detecting change on a continuous basis (Beltran Abounza, 2009; Chen *et al.*, 2010; He *et al.*, 2011; Nielsen *et al.*, 2008; Ramoelo, 2007; Verbesselt *et al.*, 2010). But, these methods only represent changes in discrete manner without representing the direction of changes. Nielsen *et al.* (2008) proposed the continuous method to detect land cover changes but he used multi-temporal imagery of irregular time period. A combination of two or more methods is used by several researchers to improve the precision of change detection (Li *et al.*, 1998; Petit *et al.*, 2001) but these methods are complex (Gong, 1993). Among all the researched methods, there is only one change detection technique available which uses long term, regular and high frequency imagery coupled with representation of changes in continuous units thorough hyper-temporal imagery analysis (Srivastava, 2011).

1.2 Prototype method

Twente University, ITC department (Srivastava, 2011) proposed a new automated method to generate land cover change maps, through hyper-temporal satellite imagery analysis at pixel level. The method monitors behaviour of change through time at pixel level and detects rapid as well as gradual cover changes that reflect either cover conversion or modification. In this method the change is defined as variation in the NDVI values of land cover, concerning the changes in proportions of land cover attributes like trees, shrub, bare soil, stone and litter. Required input data for this method are two different time series of hyper-temporal images, one as “reference period” while the second one is used for change detection called “cover change assessment period”. Land cover changes are detected using pooled standard deviation out of standard deviation of reference period.

The advantages of this method are:

1. Use continuous long term hyper-temporal NDVI imagery.
2. Quantify the changes in term of probabilities.
3. Represent land cover changes in continuous values.
4. Location of changes.

5. Commencement of changes ("when pixels start behaving as a change pixels within a specified time period"(Srivastava, 2011)).
6. Provide user-friendly interface.

This prototype method calculates land cover changes considering some preliminary user-settings (Figure 1). It includes using "period within the year" to track seasonal and inter-annual changes and pooled standard deviation (SD) values setting in term of "threshold" to show at which level changes are assessed. The "period within the year" varies from 1 to 12 months and the values of "threshold" ranges from 1.0 to 3.5 with the step of 0.5.

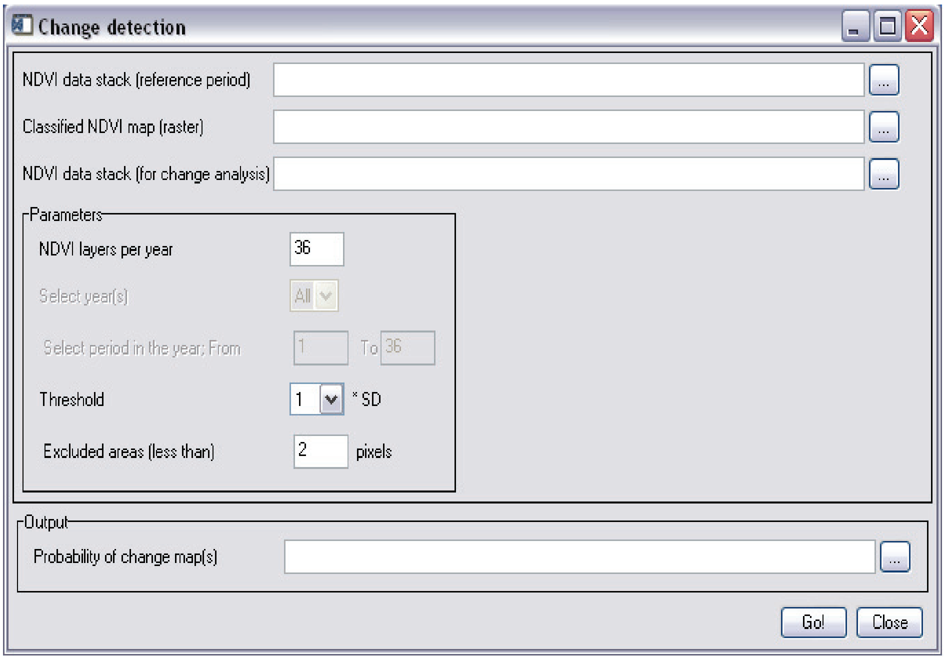

Figure 1: User interface of the prototype method.

This research was built on this prototype method. This study developed an approach to generate more accurate land cover change maps based on hyper-temporal images and the preliminary user-settings. Also a field-based accuracy analysis with the help of high resolution imagery was performed to assess the impacts of these user-settings. Statistical indicators were used to provide accuracy estimates.

1.3 Research justification

Upon reviewing the advantages of the prototype method, it has the potential to be employed and used for different areas, and provides essential information for scientists, planners and policy makers. In order to use this prototype method in an appropriate way, users need reliable output data (land cover change maps). Since the proposed method is a novel approach, there was not sufficient information about the importance of the preliminary user-settings of this method (Figure 1) and how this method was sensitive to these user-settings. Therefore, it was essential to evaluate the prototype method with different user-settings, assess the accuracy of the generated land cover change maps with respect to these settings, offer necessary choices in method settings and provide guidelines for users.

1.4 Research objective

To assess the impact of user-settings on generated land-cover change maps through the prototype method and to find the best choice of user-settings.

1.5 Research questions

1. Are the simulated land cover change maps sufficiently different when user-settings are changed?
2. Do the estimations of change derived from field data (observed changes) show sufficient variability between 1 km^2 pixels?
3. How do the simulated changes correlate with observed changes for different user-settings?

1.6 Research hypotheses

Related to research question 3:

H_0: There is a low correlation between simulated land cover changes and observed changes ($R^2 < 0.75$).

H_1: There is a high correlation between simulated land cover changes and observed changes ($R^2 \geq 0.75$).

1.7 Research assumptions

1. The default values for the user-settings are:
   “period within the year” = “whole year”
   “threshold” = 1 * SD
2. According to the crop calendar for field crops in Andalucia, growing season starts in January and ends in June (Khan *et al.*, 2011).
3. The fractions of land cover components estimated in field work are sufficient for this study to use as interpretation of changes.

2. Materials and Methods

2.1 Study area

Andalusia with an extent of 87,268 km^2 is located in the South of Spain (Figure 2). It is the second largest autonomous community in Spain with 8 provinces and 770 municipalities. It has a Mediterranean climate with hot, dry summers and mild, rainy winters. The average temperature in Andalusia throughout the year is over 16 °C.

The typical vegetation of Andalusia is Mediterranean woodland and the dominant species are: Holly oak, Cork oak, pines and Spanish Fir. The major crops are wheat, rice, maize, sunflower, cotton, olive, almond, orange and grapes. Agriculture is very important in Andalusia and 67% of this region is utilized for agricultural purposes (Khan*, et al.*, 2011).

Figure 2: Study area: Andalucia, Spain.

2.2 Data used

Available hyper-temporal data for this study were SPOT4 and SPOT5 vegetation sensors, 10-day MVC (Maximum Value Composite) NDVI images with 1 km^2 resolution from 2000 to 2004 (180 images) as “reference period” dataset and 2009 (36 images) as “cover change assessment period” to detect changes. The dataset were obtained from the SPOT Vegetation website (www.vgt.vito.be).

Orthophotos of 2004 with a pixel resolution of 1 meter, orthophotos of 2008/2009 with pixel resolution of 0.5 meter and field data conducted in 2011 were available for up-scaling the observed land cover components to pixel resolution of 1 km^2 of imagery. Orthophotos were downloaded from the website http://www.juntadeandalucia.es/index.html.

2.3 Software and hardware used

The following technical software applications and hardware were employed in this research:

Table 1: Software and hardware used.

Software	Usage
ERDAS IMAGINE 2011	To perform image processing
ArcGIS 10	Data preparation, analysis, map composition
Definiens eCognition 8.64	To implement image segmentation
ENVI-IDL 4.8	To perform image processing
Change detection tool	To create simulated land cover change maps
MATLAB 2011	To do statistical analysis
SPSS	To do statistical analysis
Arcpad	To record the surveyed points details during field work
Tom Tom	To navigate during field work

2.4 Method

The whole research process was divided into five phases: i) Data preparation, ii) Simulated change estimation, iii) Field data collection, iv) Observed change estimation and v) Regression analysis.

2.4.1 Data preparation

The 10-day MVC SPOT-Vegetation NDVI images were stacked and arranged into two time periods (Figure 3). The first time period (“reference period”) was from January 2000 to December 2004 (180 layers). The second time period was ranging from January 2009 to December 2009 and was called "cover change assessment period" to be compared with the "reference period" for change calculation. The NDVI datasets were geo-referenced, de-clouded and cleaned from noise using an "Adaptive Savitzky-Golay filter" (ASAVGOL).

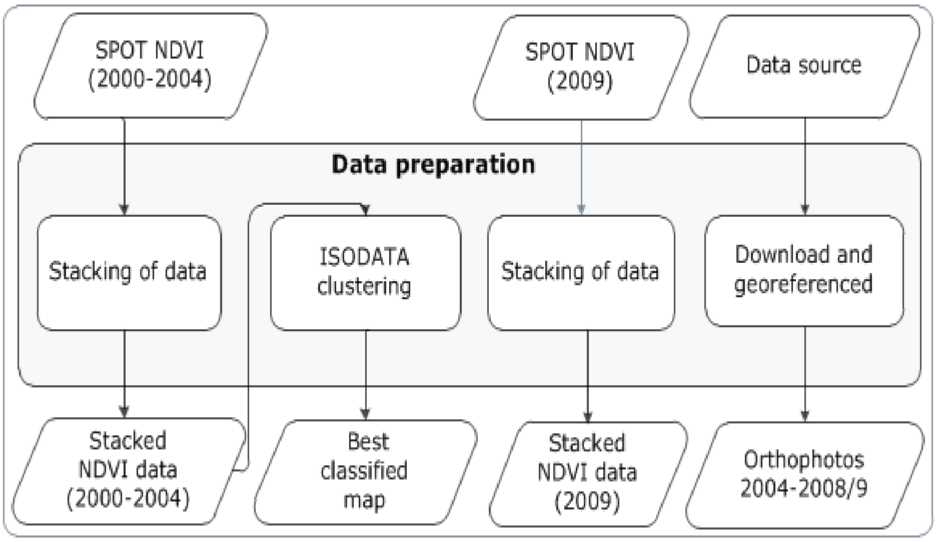

Figure 3: Data preparation flowchart.

According to Skidmore *et el*. (2006) de-cloud means "using by image and pixel the supplied quality record, only pixels with a 'good' radiometric quality for bands 2 (red; 0.61-0.68 µm) and 3 (near IR; 0.78-0.89 µm), and not having 'shadow', 'cloud' or 'uncertain', but 'clear' as general quality, were kept (removed pixels were labelled as 'missing')".

An "Adaptive Savitzky-Golay filter" (ASAVGOL) method used for removing the effect of noises was based on "Savitzky-Golay filter" (Beltran Abounza, 2009; Jönsson *et al.*, 2004). The "Adaptive Savitzky-Golay filter" (ASAVGOL) is based on ordinary least square fit methods to fit the upper envelope of the vegetation index (Jönsson*, et al.*, 2004)

The methodology given in de Bie, *et al.* (2008) were followed to produce the best classified map from NDVI stacked layers of reference period (2000-2004). According to this methodology ISODATA (Iterative Self-Organizing Data Analysis Technique) unsupervised clustering procedures and divergence statistics were performed using ERDAS software. To select the best classified map, both minimum and average divergence values should be high and the number of classes should remain limited (de Bie, *et al.*, 2008). The minimum divergence shows the similarity between the two most similar classes and average divergence shows the similarity among all the classes (de Bie, *et al.*, 2008). The best classified map was used as base map to calculate changes in cover change assessment time period through the prototype method.

2.4.2 Simulated change estimation

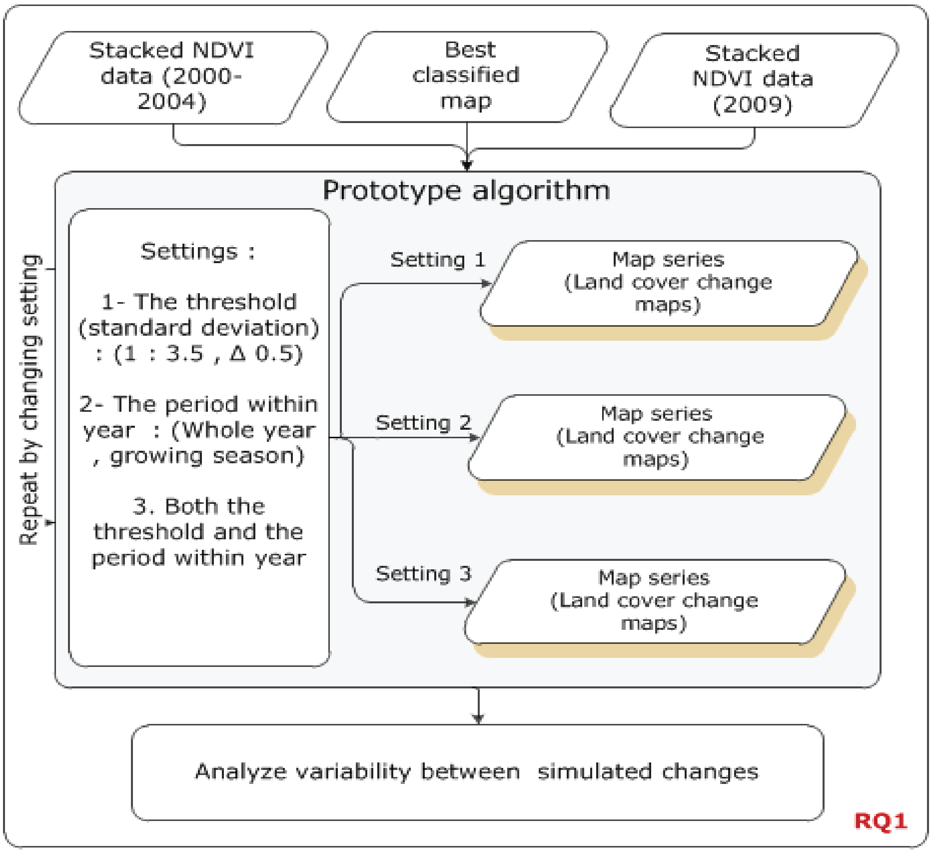

Figure 4: Simulated change estimation flowchart.

The generated inputs, 1) NDVI data of 2000-2004 as “reference period”, 2) NDVI data of 2009 as “cover change assessment period” for change analysis and 3) best classified map were processed using the prototype method. A series of annual change maps were generated by repeating the method for each setting according to Table 2.

Table 2: The process of repeating prototype method.

run	threshold(SD)	period within the year	Number of iterations
1	1-3.5 , Δ0.5	default value	6
2	default value	the whole year and growing season	2
3	1-3.5 , Δ0.5	the whole year and growing season	12

A series of generated maps produced the change values per pixel, to rescale these values to a 0 to 1 range and normalized changes, the change values for all pixels of each generated map that covered the surveyed field data were divided by their maximum change value.

To study whether the generated maps are sufficiently different with respect to different choice of user-settings, the change value for all pixels of generated maps that cover survey field data were compared graphically through box plots.

2.4.3 Field data collection

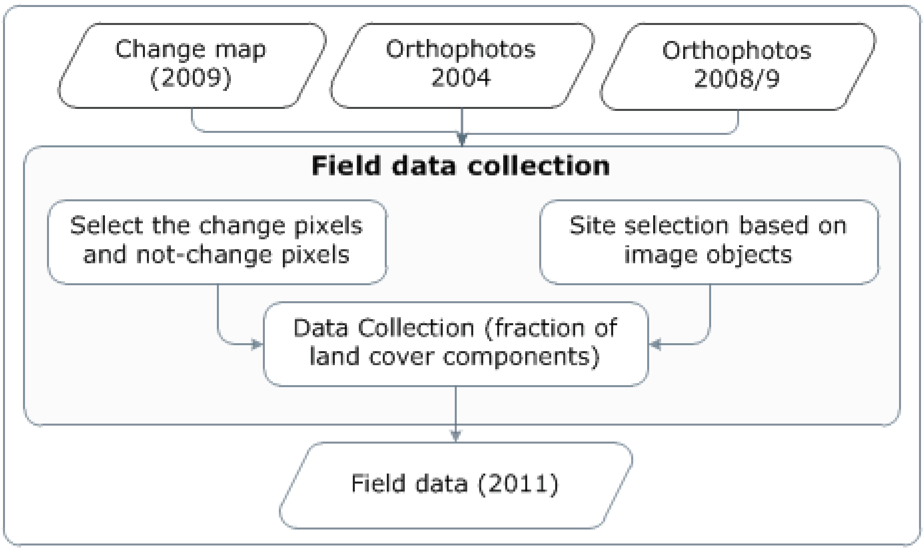

Figure 5: Field data collection flowchart.

Prior to field work a land cover change map of 2009 with default user-settings was generated through the prototype method (Figure 6). The areas with high changes which were not covered by survey in previous field work periods were identified and selected as sample areas. Random clustered sampling scheme was used to select pixels to visit in the field work. Orthophotos of the corresponding areas were used for site selection based on image objects.

During the period from 18th of September to 2nd of October 2011 field data collection was carried out in the chosen areas and changed as well as non-changed pixels were visited (Figure 5). The sample unit was considered to be a 1 km^2 so that it corresponds with the SPOT Vegetation pixel size. Land cover characteristics of each image object including percentages of trees, shrubs, grass / herb, stone, litter, soil and life form as well as non-vegetated aspect of image objects (water, built-up area) and coordinates were collected (See Appendix 1). The reasons of change for changed pixels were studied. In total 60 pixels were surveyed and 530 sample points were taken.

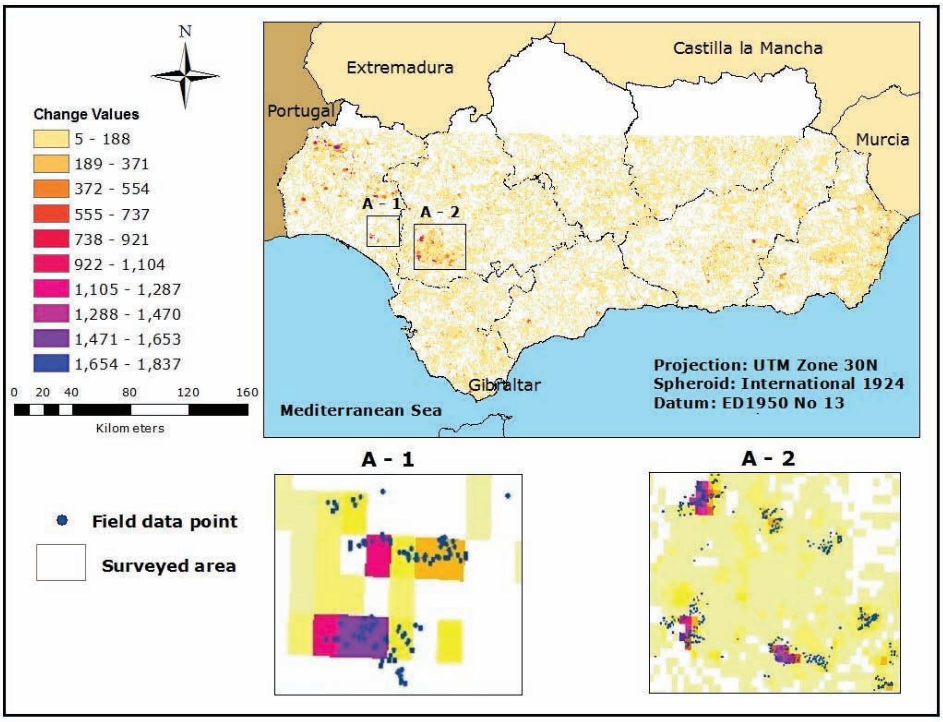

Figure 6: Land cover change map (2009), two surveyed areas with field data points are also shown.

2.4.4 Observed change estimation

In this step the orthophotos of 2004 and 2008/2009 along with the surveyed points of 2011 were used to calculate the observed land cover change in surveyed pixels (Figure 7). To estimate observed change from 2004 to 2008/9 a semi-automated procedure based on the following four steps were performed: i) Legend preparation, ii) Orthophotos segmentation, iii) Segmented image classification and iv) Observed change estimation.

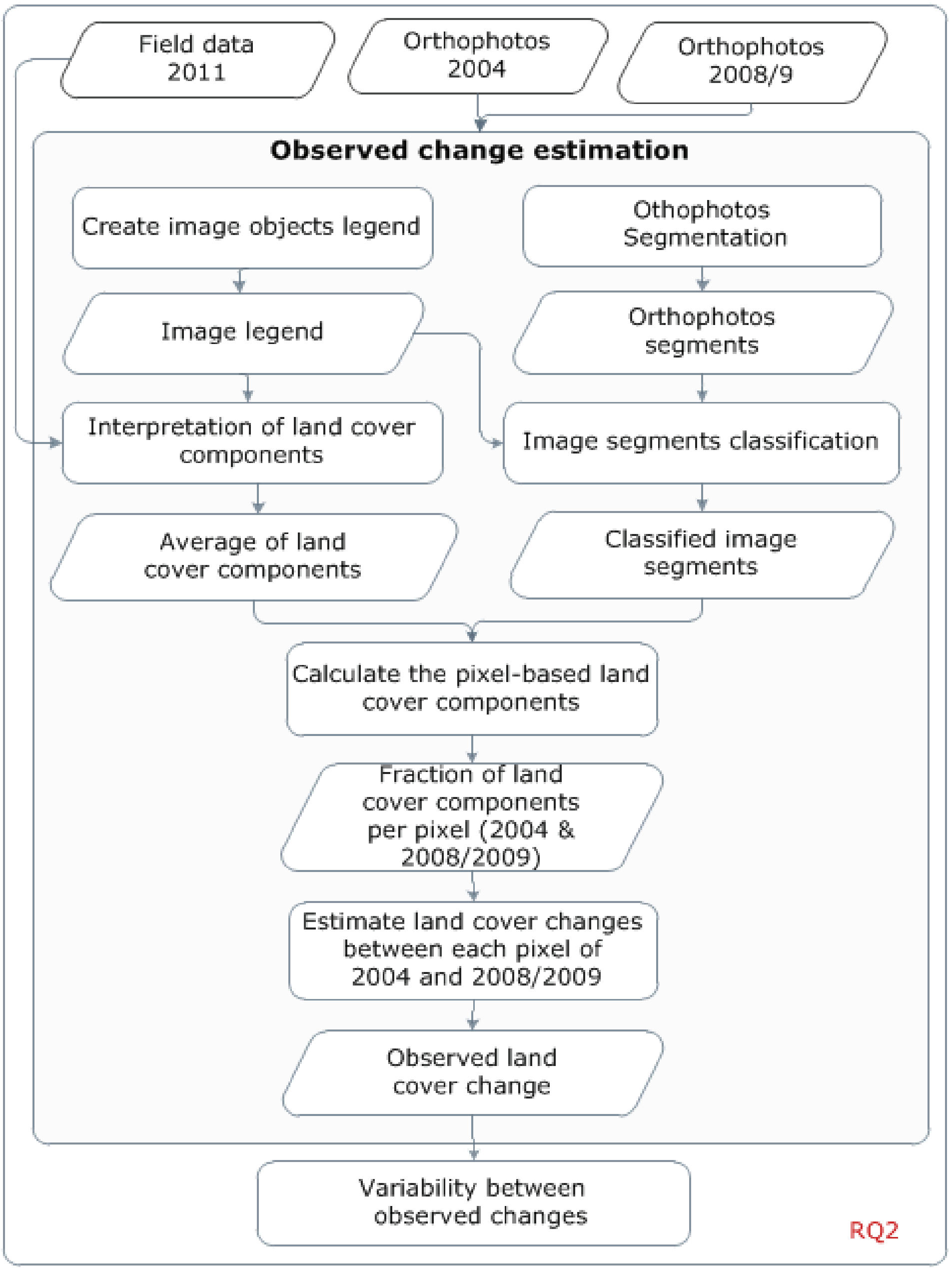

Figure 7: Observed change estimation flowchart.

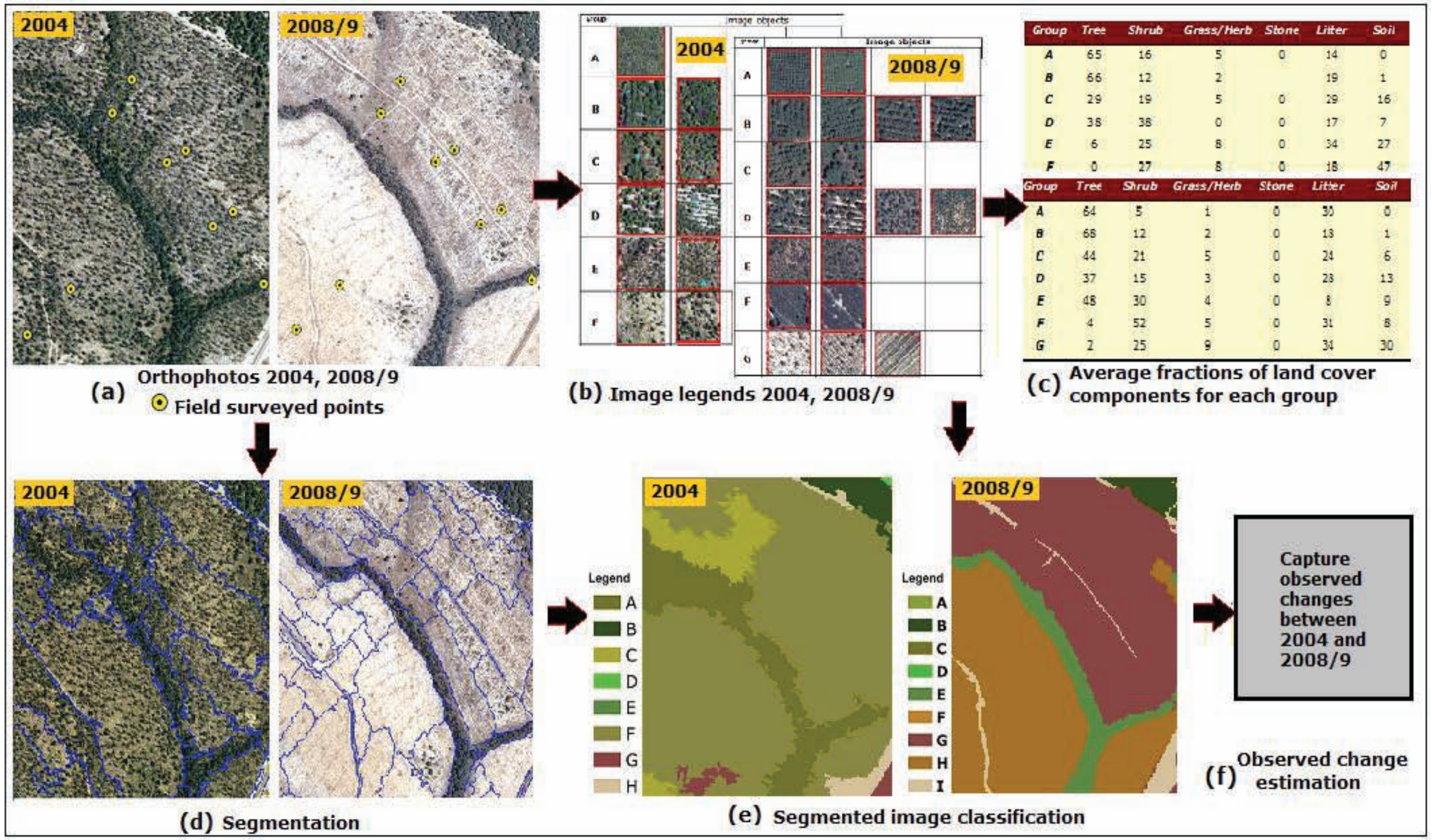

Figure 8: Summary of the steps included in estimation of observed changes.

i. Legend preparation

First step in interpretation of the orthophotos was legend preparation. The legends were established from the visual interpretation of both 2004 and 2008/2009 orthophotos with the help of field surveyed points in September 2011 (Figure 8, a). The 2004 legend was made using only non-change surveyed points which were presented outside the change pixels. Image legend of 2008/2009 was made using all surveyed points.

Using photo interpretation, different image objects based on 2004 and 2008/2009 orthophotos were identified and the objects were divided into different groups considering their colours, textures and patterns. Similar image objects were put into the same group. An identification code was assigned to each group (Figure 8, b).

Using surveyed points, the average fraction of land cover components (fraction of trees, shrubs, grass/herb, stone, litter and bare soil) in a group was calculated and average fractions of land cover components were assigned to each group (Figure 8, c). These groups with their descriptive information were considered as final image legend.

ii. Orthophotos segmentation

Object oriented strategy was applied to implement orthophotos segmentation with eCognition software. Throughout the "Multi-Resolution Segmentation"(MRS) method (segmentation procedure) at pixel level, orthophotos segments were generated for all orthophotos based on several adjustable criteria such as homogeneity and heterogeneity in shape, size and colour. To obtain the parameters that generate the best segmentation (meaningful objects), weights of shape, scale and compactness were changed.

In order to get the best segmentation result, all parameters were tested through a trial-and-error and different values were applied to the parameters, according to the Table 3:

Table 3: eCognition parameter settings.

Shape	Compactness	scale
0.1	0.5	150
0.9	0.5	250
0.5	0.5	250

The segmentation results with their embedded attributes were exported as shape files through eCognition software (Figure 8, d). These attributes were:

1: Layer value: Brightness and Mean value of three layers
2: Texture: Homogeneity and Contrast

These attributes were later on used in the classification step.

iii. Segmented image classification

"K-mean" classification using brightness, mean value of three layers, homogeneity and contrast attributes was performed through SPSS to classify generated image segments. The classification was iterated 50 times to define 35 classes. The supervised grouping based on image legends was done and these 35 classes were further generalized using image object legend into less number of classes depending on heterogeneity of the image objects. Manual editing and some corrections were performed after the classification (Figure 8, e). Finally, average fraction of different land cover components was assigned to each segmented class.

iv. Observed change estimation

To estimate the observed changes, up-scaling the surveyed points to the pixels resolution of 1 km^2 (SPOT pixel) were performed through the following steps (Figure 8, f)):

- To calculate total fractions of land cover components per pixel, the classified image segments were intersected with all pixels that covered the 2011 surveyed points. Area fractions of each image segment within each pixel were calculated (Equation 1).

  *Area fraction = (Image Segment Area / Area of SPOT pixel) * 100*
  (Equation 1)

  Where:
  - "Area fraction" is the fraction of an area covered by each image segments of orthophotos within an SPOT pixel.
  - "Area of SPOT pixel" is total area of all image segments within a SPOT pixel (1 km^2).

- The total fraction of each land cover components were calculated using the Equation 2.

$$\textit{Pixel-based land cover component fraction} = \sum_{i=1}^{n}(\textit{Area fraction} * \textit{proportion of each land cover component}) \,/\, 100$$
(Equation 2)

Where

- "Pixel-based land cover component fraction" is total fractions of each land cover components per pixel.
- "i" is the index of image segments within a SPOT pixel.
- "n" is the number of segments.

- To estimate observed change of each pixel from 2004 to 2008/2009 the Bray-Curtis dissimilarity method (Bray *et al.*, 1957) was used (Equation 3) between 2004 and 2008/2009 "pixel-based land cover component fractions" . In the Equation 3, the sum of absolute difference between total component fraction of all land cover components were divided by the sum of total component fraction of all land cover components per pixel.

$$BCD_{(i,j)} = \frac{\sum_{k=0}^{n-1}|Yi,k-Yj,k|}{\sum_{k=0}^{n-1}(Yi,k+Yj,k)}$$ **(Equation 3)**

Where

- BCD is the dissimilarity between all land cover components in each pixel from 2004 and 2008/2009
- 'Y': land cover component fraction (fraction of trees, shrubs, grass/herb, stone, litter and bare soil)
- 'k': index of a land cover component
- 'i': index of pixels from 2004
- 'j': index of pixels from 2008/2009.
- 'n': number of pixels.

The Bray-Curtis Dissimilarity (BCD) is a non-parametric method which calculates robust and reliable dissimilarity results for a wide range of applications and is widely used in ecology and environmental sciences (Schulz, 2007). This BCD value is bound between 0 and 1. A value of 0 shows a complete similarity between two data records and a value of 1 means two data records are completely different. Also, from the dissimilarity value, Bray-Curtis Similarity (BCS) can be easily calculated (Bray, *et al.*, 1957):

$$BCS = 1 - BCD$$ **(Equation 4)**

The statistical analysis was done to determine there is sufficient variance between observed changes within 1 km^2 pixels.

2.4.5 Regression analysis

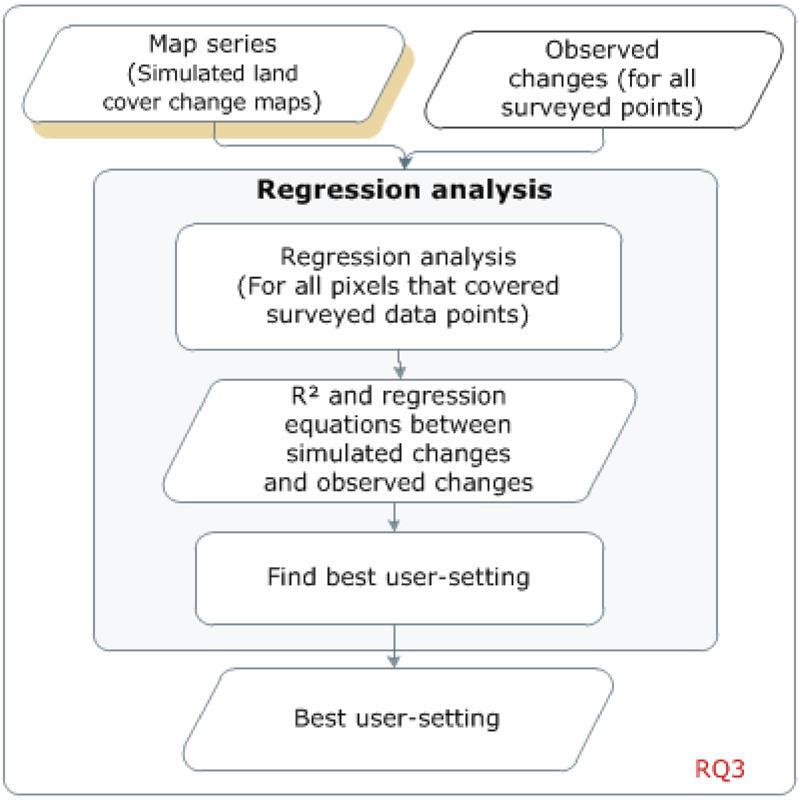

Figure 9: Regression analysis flowchart.

To investigate the impact of different choices of user-settings on the accuracy of generated land cover change maps through the prototype method, field-based analysis and statistical approach was performed on all pixels of the generated maps that cover the surveyed points (Figure 9).

Observed changes and simulated changes were used to apply a simple linear regression analysis. Scatter plots showing by pixels (simulated changes versus observed changes) were drawn per user-setting to show the relation between simulated changes and observed changes. Using regression model and scatter plot showing by pixels (simulated changes versus observed changes); coefficient of determination (R^2), regression equations and 1:1 lines along with regression line was considered in order to assess the accuracy of the models.

To find the best user-setting which generates the most reliable maps, R^2 and regression equations were compared. The criteria for selecting the best user-setting were:

1. High R^2 value.
2. Linear regression model which crosses the origin (in regression equation, absolute value of intercept should be close to 0).
3. Good fitness between regression line and 1:1 line.

3. Results

This chapter presents the obtained results arising from the assigned methodology approach.

3.1. Simulated change estimation

The simulated land cover changes of 60 pixels of 1 km^2 which were covered by surveyed points were compared. Table 4 shows the maximum values of each simulated change map for these 60 pixels according to different choice of user-settings also in combination with the number of pixels with a normalized simulated change value of greater than defined threshold of 0.5. The maximum change values show various ranges of simulated changes according to each user-setting and indicate significant differences among them. The number of pixels with normalized change value of greater than 0.5 present the distribution of pixels above this threshold and show how the distribution of pixels differ for each user-settings. The results (Figure 10, Figure 11, and Table 4) show that by increasing the threshold (SD) the range of change values decreases. The ranges of simulated changes are higher in case of “whole year” in comparison with “growing season”. The results clearly verified the sensitivity of the prototype method to different choice of user-setting and represent how the simulated changes sufficiently vary by changing different choice of user-settings.

Table 4: Maximum change values according to the different choice of each user-setting and number of pixels with normalized change value of greater than 0.5.

User-settings		**Maximum value**		**No. of pixels with normalized simulated change value > 0.5**	
“period within the year”		whole year	Growing-season	whole year	Growing-season
“threshold (SD)	1.0	1485	1024	20	17
	1.5	1247	899	19	17
	2.0	1018	780	17	14
	2.5	801	662	14	13
	3.0	612	612	14	11
	3.5	470	456	11	9

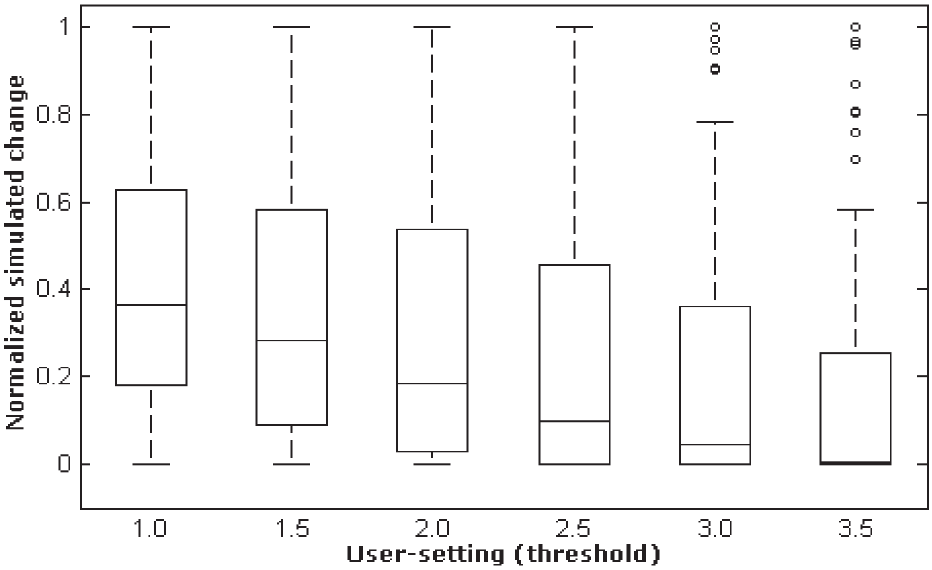

Figure 10: Simulated changes boxplot (2009 - whole year). Number of pixels: 60 pixels which were covered by surveyed points.

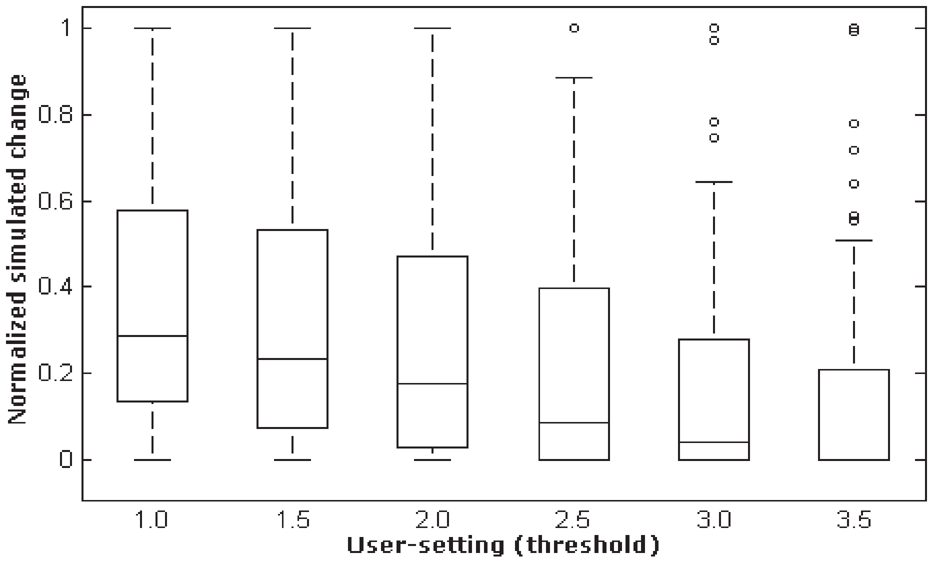

Figure 11: Simulated changes boxplot (2009 - growing season). Number of pixels: 60 pixels which were covered by surveyed points.

3.2. Observed change estimation

Observed land cover changes were estimated using the following four steps:

i. Legend preparation

Due to the different characteristics of 2004 and 2008/2009 orthophotos, two image legends were independently generated. The legend of 2004 was composed of 14 different image object groups and image objects in the 2008/2009 legend were divided into 20 groups. The results can be reviewed respectively in Appendix 2 and Appendix 3. Regarding the image legends, average fractions of land cover components (fraction of trees, shrubs, grass/herb, stone, litter and bare soil) were assigned to each group.

ii. Orthophotos segmentation

All possible combinations of weights for segmentation parameters were tested. By applying a weight of 0.1 to shape, 0.5 to compactness and 150 to scale, the images were over-segmented and too many small image objects were created (Figure 12, a). By setting a weight of 0.9 to shape, 0.5 to compactness and 250 to scale, the images were under segmented and some large image objects (mix of two or three image objects) were generated (Figure 12, c). The best result was obtained when equal weight of 0.5 was set to shape and compactness and 250 was applied to scale (Figure 12, b).

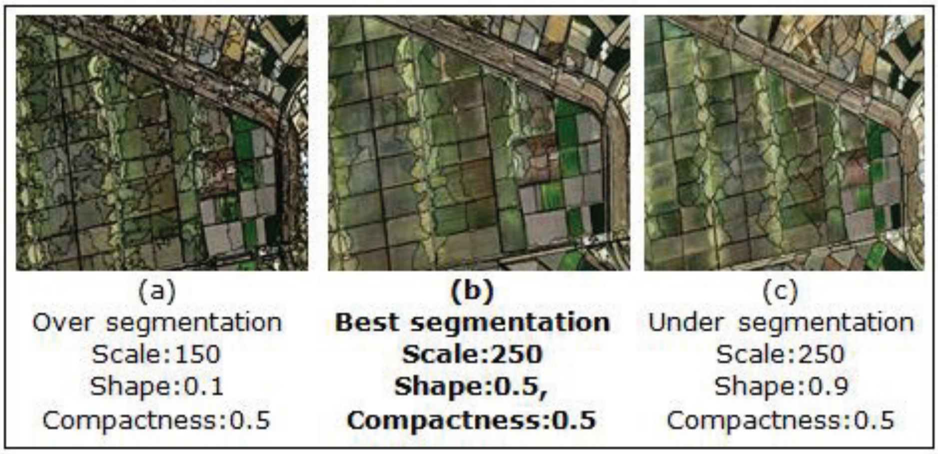

Figure 12: Segmentation result using different parameters.

iii. Segmented image classification

Classification results of pixels of 2004 and 2008/2009 orthophotos having natural and semi-natural land cover are illustrated in Figure 13 to visualise the land cover changes that happened between 2004 and 2008/2009.

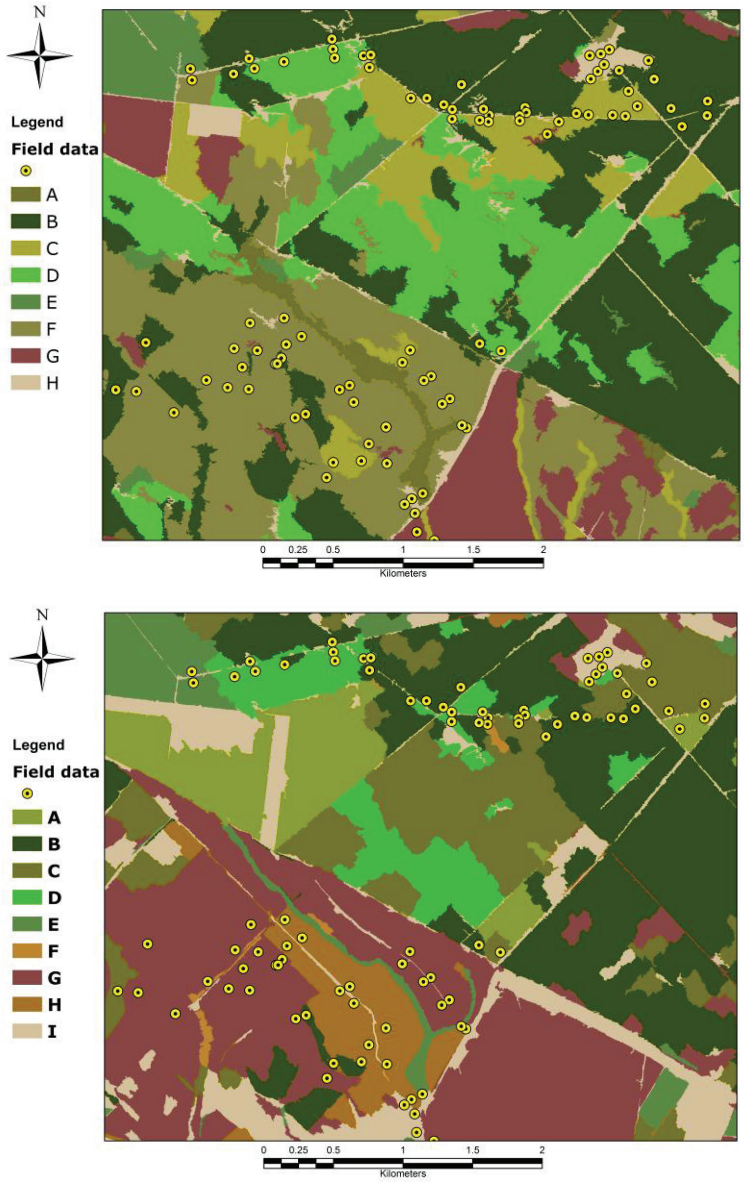

Figure 13: Segmented image classification result. 2004 (top) and 2008/2009 (bottom).

iv. Observed change estimation

The result of observed changes of 60 pixels of 1 km^2 between two time periods (2004 and 2008/2009) shows that the maximum observed change value was 0.4 and the least value was 0.015. The histogram (Figure 14) shows variability between observed changes of all assessed pixels and indicates the normal distribution between limited range of 0.015 and 0.25. Although the range of observed changes was limited and the standard deviation was rather low (0.07) variation between observed changes was sufficient for this study.

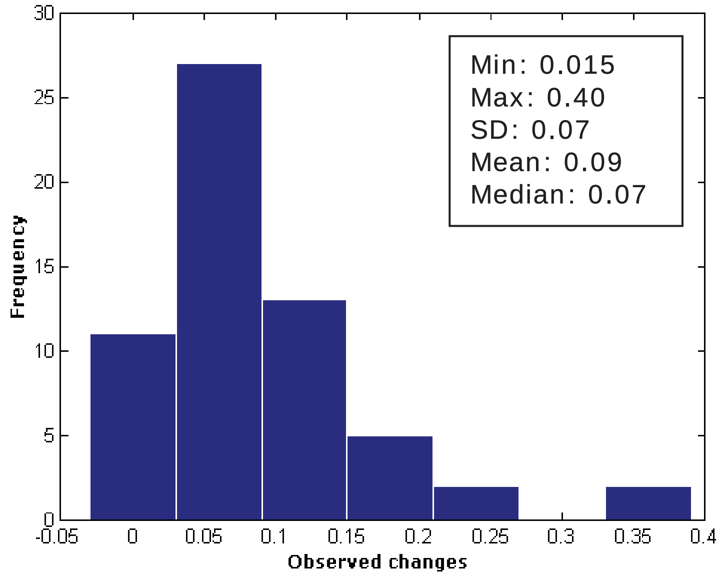

Figure 14: Histogram of observed changes.

3.3. Regression analysis

The results of regression analysis between simulated changes versus observed changes for each user-setting per pixel show a very weak agreement (See Figure 18 and Figure 19 in Appendix 4). The results show that observed change values of some pixels with agricultural land cover were very low while simulated change values of their corresponding pixels showed very high changes. Studying the ETM images of these areas emphasized that drastic changes happened in these areas through the years (Figure 15). The ETM images illustrate that these high changed pixels cover areas with agricultural land cover and are formed mainly by rice fields in 2004 (de Bie, 2011; personal communication).

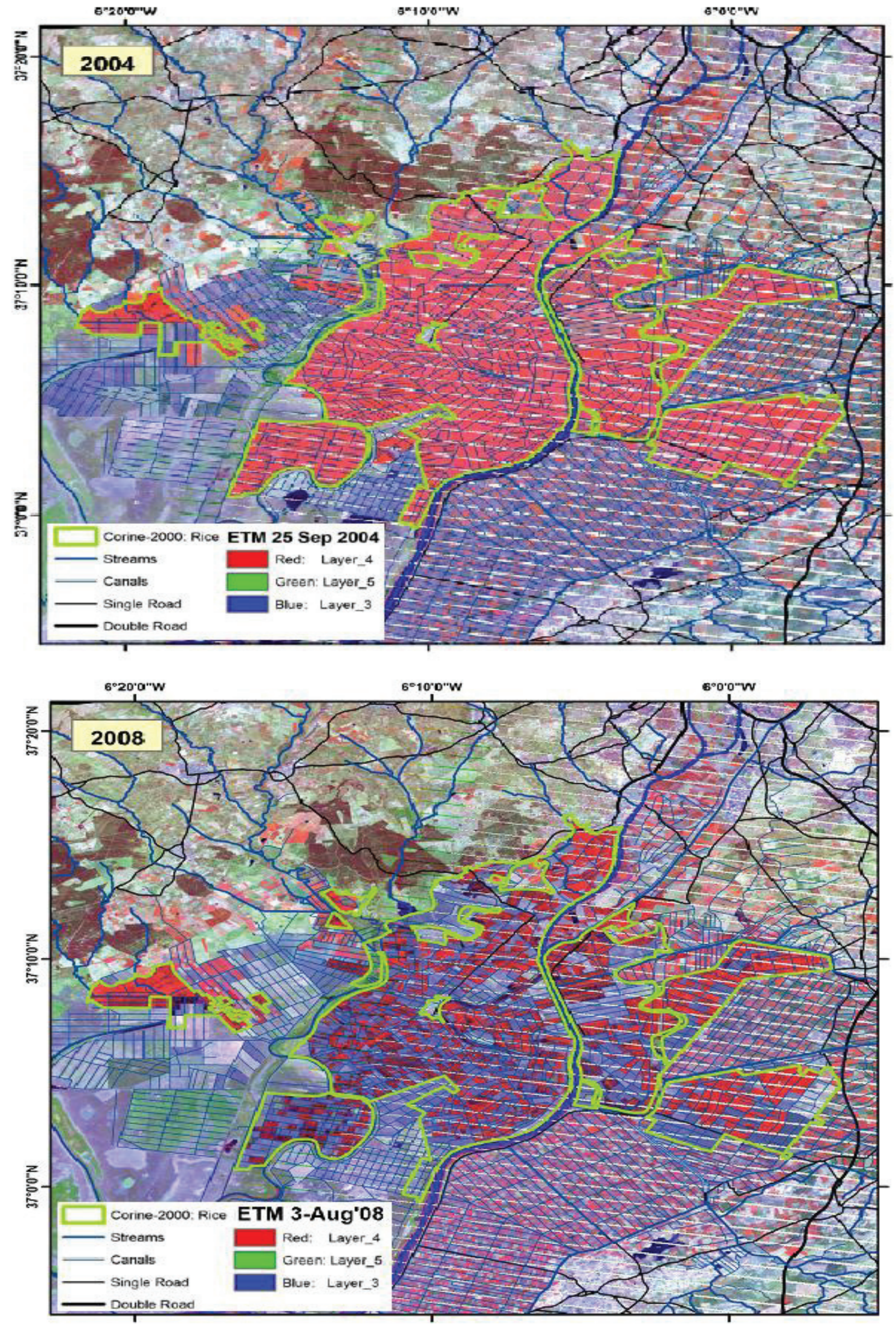

Figure 15: Rice areas in Sevilla, Andalucia (2004 and 2008 ETM images) (de Bie, unpublished work).

Regarding the above problem, pixels were split in two different groups, pixels with agricultural land cover patterns and pixels having natural or semi-natural land cover. The linear regression analysis was repeated and limited to 28 pixels related to natural and semi-natural land cover. The generated models through “growing season” choice of “period within the year” user-setting were not considered as well, considering the mismatch problems between the aerial photograph dates and the field data collection dates (de Bie, 2011; personal communication).

Figure 16 illustrates relations between simulated changes versus observed changes considering different options of “threshold” user-setting. Comparison between R^2 values of each regression model (Figure 16) show that the highest values of R^2 are related to the models generated through “threshold” of “2.5”, “2.0”, “3.0” and “1.5” with 92%, 89%, 88% and 85% goodness of fit, respectively. Comparison between regression equations show that the equation of the model generated through threshold of “1.5” has the nearest intercept value to zero with absolute intercept value of 21. The comparison between regression lines with 1:1 lines (Figure 16) represents the goodness of fit between simulated changes and observed changes. The graphs (Figure 16) show an over-estimation in simulated changes when “threshold” was equal “1.0”. The “threshold” of “1.5” indicates the high agreement with observed changes while regression line is close to 1:1 line and highly fitted. The result represents minor under-estimation of simulated changes when “threshold” of “2.0” was chosen. Under-estimation of simulated changes gradually increase by increasing “threshold” from “2.0” to “3.5” and it shows that the prototype method does not consider the minor changes. According to the above mentioned comparisons, the generated model through the user-setting with “threshold” equals “1.5” shows the strongest agreement between simulated changes and observed changes and these user-settings (Table 5) produce the most accurate land cover change map.

Table 5: Best choice of user-settings.

User-setting	choice
“threshold” (SD)	1.5
“period within the year”	Whole year

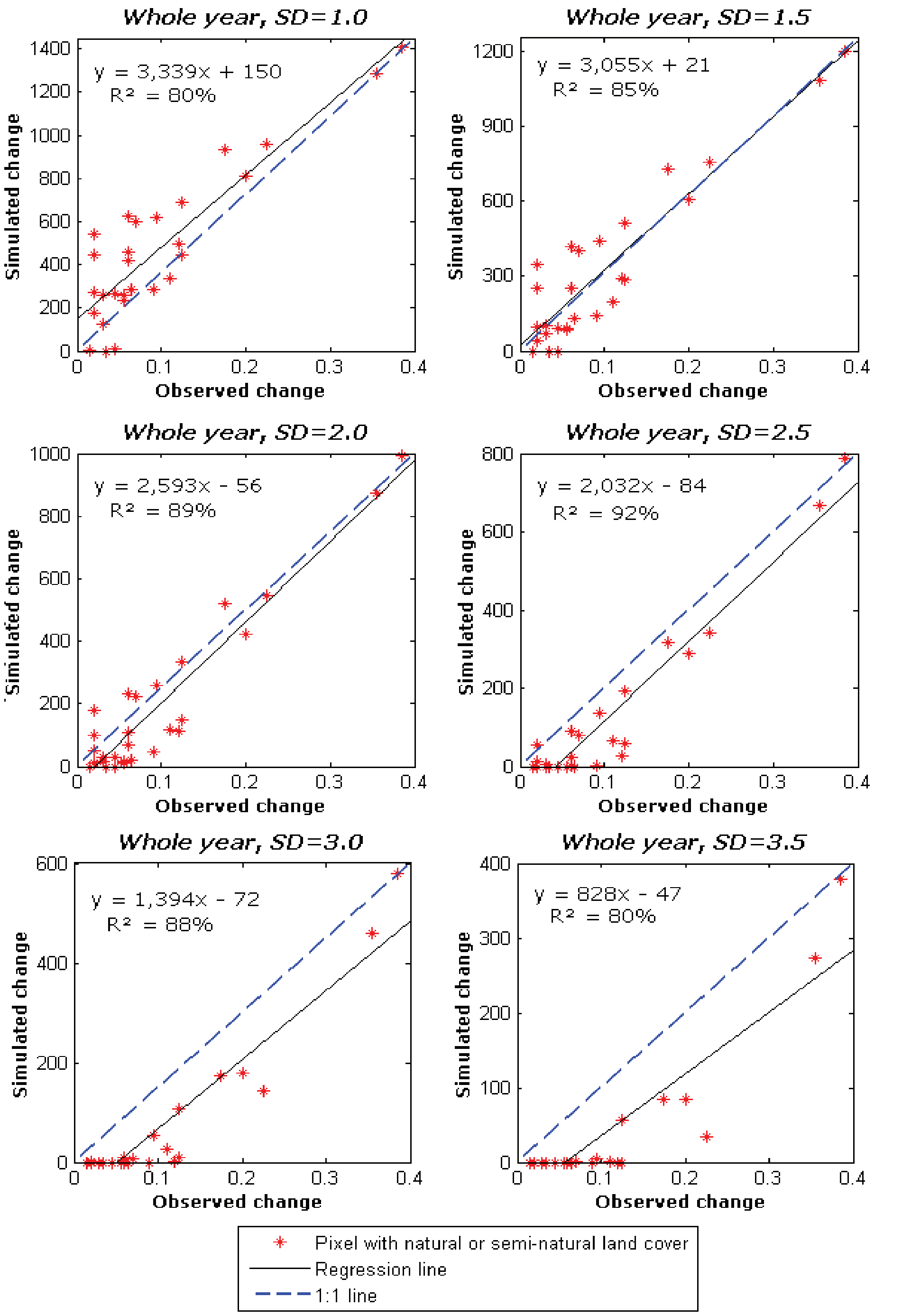

Figure 16: Simulated changes versus observed change (2009-whole year), 28 Pixels with natural and semi-natural land cover.

4. Discussions

In this chapter, the achieved results are discussed.

4.1. *Simulated change estimation*

The importance of the user-settings was successfully checked and it was found that this method is highly sensitive to these user-settings which make it effective to use in different scenarios of land cover change. Regarding different choice of user-settings, the prototype method generated different change values beyond certain ranges (from zero to maximum value) (Table 4) and, these ranges decreased by increasing the threshold (SD). The result showed that (Table 4, Figure 10, Figure 11) by increasing the threshold (SD) distribution of pixels increased beyond the defined threshold of 0.5. Minor changes were ignored by the prototype method and only pixels with high changes were considered and the change values under-estimated for user-settings with threshold of “2.5”, “3.0” and “3.5”. Under-estimation of changes is higher in case of “growing season”. Obtained results showed that the generated land cover change maps through the prototype method concerning different user-settings are sufficiently different. This study confirmed the importance of these user-settings for the prototype method and emphasized that different choice of the user-settings do influence on generated land cover change maps.

4.2. *Observed change estimation*

i. Orthophotos segmentation

Aerial photographs provide essential information about past and present ground features on large areas (Gennaretti *et al.*, 2011). Also, the comparison between land cover maps generate through aerial photograph represents that they are reliable sources for understanding land cover (Gennaretti, *et al.*, 2011). There are different approaches to extract land cover information from aerial photographs. The common procedure is based on photo interpretation to make an image legend and then manual digitizing. Manual digitizing of photos is a time consuming method for the study of large areas. Also, the result may not be precise enough due to user interventions. The new approach is object-oriented, and several studies prove the advantages of this method (Burnett *et al.*, 2003;

Gennaretti*, et al.*, 2011; Tansey *et al.*, 2009; Zhou*, et al.*, 2008). This method focuses on segmentation of aerial photographs.
Although segmentation of aerial photos was not one of the objectives of this study, it was one of the most critical tasks in this study because it provides the basis to estimate observed change. The more accurate the segmentation result the more accurate the observed change estimations. In this study, the segmentation process was carried out using the eCognition. eCognition manages the segmentation procedure by assigning weights to different parameters; the most important parameters are “scale”, “compactness” and “shape” and results of segmentation highly depends on defined weights for these parameters (Aminipouri *et al.*, 2009). There is no standard solution to reach the optimal segmentation, and to achieve a satisfactory segmentation result, different segmentations must be performed according to different selections of weights for “scale”, “compactness” and “shape” through trial and error process (Zhang *et al.*, 2006). The qualitative assessment of the best segmentation result presented in this study was done visually.

ii. Observed change estimation

The result of observed changes showed that the maximum value of observed changes between all assessed pixels was 0.4. It showed that in this study the pixels with highest changes in Andalucia region never counted and all assessed pixels did not change completely (100% actual changes). Complete land cover change or “land cover conversion” reflects a complete land cover change from one major land cover class to another (Coppin *et al.*, 2004a) which occurred in an area due to fire, urban development and etc. Pixels of 1 km^2 areas are vast areas and consist of different land cover patterns such as farms, fields, forest and so on, and changes in some land covers of a pixel do not lead to high change in the whole pixel area. The range of 0.015 to 0.4 showed that changes happened in the assessed areas but not extreme changes and it was verified from field work.

With accepting this fact that this study has limited data and also the range for observed changes were limited but it provided enough data for this study and the normal distribution of observed changes between 0.015 and 0.25 was quite acceptable and it was supported that observed changes were sufficiently different between 1 km^2 pixels.

4.3. Regression analysis

The dynamic nature of agriculture, like seasonality and its occurrence almost everywhere are the strongest incentives for scientists to monitor agriculture from space (de Bie *et al.*, 2000). The seasonal variations of the agricultural land covers affect the ease of interpretation. Aerial photographs are statistics and do not have the potential to show dynamic nature of the agricultural land covers, thus it needs multi-temporal images for accurate interpretation.

In this study for all assessed pixels representing natural, semi-natural or agricultural land covers, very weak agreement between simulated changes versus observed changes considering different choice of user-settings was seen. The estimated observed changes in some areas having agricultural land cover showed minor changes, while the method showed drastic changes in the same areas. The reasons for such a big difference might rise from the problem of mismatch between the date orthophotos were taken and the field data collection date. Field data collection was done at the end of September 2011 with the help of orthophotos of 2004 and 2008/2009. According to the growing season calendar in Andalucia, normally crops are in the fields from January to June (Khan, *et al.*, 2011). To solve this problem, substantial information in terms of images was essential to interpret changes. The study of the ETM images of these areas (Figure 15) showed that rice crop was dominant in these areas but over years distinct changes happened in these areas and rice was grown in abundance (de Bie, 2011; personal communication). This fact makes it unreliable to interpret areas having agricultural land cover without reliable field information or fields surveyed in growing seasons. Therefore, all the pixels which covered the areas with agricultural land cover were omitted from this study and the study only focused on areas having natural or semi-natural land cover. However, the approach for estimating the observed changes was not a proper method for the areas having the dynamic characteristics such as areas with agricultural land cover, but it worked properly for the natural and semi-natural areas.

Considering the result of regression analysis, for lower thresholds (SD) of “1.0” simulated changes were over-estimated, whereas for higher thresholds of “2.0”, “2.5”, “3.0” and “3.5”, under-estimation in the results of simulated changes happened. The model related to the threshold of “1.5” showed strongest agreement between simulated cover changes and observed cover changes with R^2 of 85%. Therefore the null hypothesis was rejected and the user-setting with threshold of “1.5” and the period of “whole year” was chosen as the best user-setting.

There might be several errors occurring in each step that affect the accuracy of the generated maps. Errors can be introduced at any steps:

1. Quality and suitability of the satellite imagery.
2. Errors in geometric and radiometric rectification process.
3. Error in field data. The main sources of error arise from error in field data collection. Field data accuracy was a major source of error in the estimation of observed land cover changes. In this study, to estimate observed changes point extrapolation process was performed using the surveyed points. In this process information from surveyed points expanded to nearby areas. Thus, an error in field points easily has influence on estimated observed changes. Error might arise from i) Field data collection in 2011 was done with the help of orthophotos of 2004 and 2008/2009. It shows mismatch between the date the orthophotos were taken and the field data collection date, ii) Data collection was not done in proper time, it was conducted at the end of September 2011 and it was not the proper time to collect data about the actual land cover components, iii) Human error in field data collection to estimate fraction of land cover components can be faulty and biased.
4. Error in legend preparation. Visual interpretation of orthophotos regarding image legends might lead to errors, although it was done very carefully.
5. Error in segmentation and classification procedures.

All these errors were accumulated and propagated to the regression analysis step and finally propagated to the final maps.

Given the limitations imposed by the data, this study proved that the prototype method performing effectively in detecting the land cover changes at pixel level and monitoring the on-going behaviour of pixels in Andalucia region. The result clearly verified that land cover change maps which were produced through the prototype method considering the best choice of user-settings have a high accuracy in areas having natural or semi-natural land covers. Thus, these choices of user-settings can be recommended as a guide-line for users in Andalucia region. This supports policy makers and researches to identify accurate annual natural or semi-natural land cover changes in Andalucia area and it makes it easier for them to set the policies and strategies.

Unlike available change detection methods (Conchedda*, et al.*, 2008; He*, et al.*, 2011; Nielsen*, et al.*, 2008; Verbesselt*, et al.*, 2010), the prototype method provides the opportunity for users to generate continuous representation of on-going land cover changes by choosing different user-settings through user-friendly interface. It improves its usability in different areas of research with different user defined settings. The prototype method allows users to generate accurate change maps at annual basis using new imagery and any reference period, the accuracy of change maps at seasonal basis have not yet confirmed and need more study in this issue in the future. The generated land cover change maps show where the changes occurred but it still needs interpretation about what land cover changes into what. This prototype method improved the utility in the term of user-friendly interface.

Considering the advantages of this prototype method, the successful achieved result in this study and take in to account that till this date no alternative method could be found for this prototype method, this prototype method has potential to be employed in the other areas. This study was the first significant result of this prototype method. There are still many challenges on this prototype method and further studies should be conducted. The best choice of user-settings might be different from an area to area, but it has not been assessed for other areas yet. Impact of the user-settings on different areas needed to be studied and the prototype method should be calibrated when it is used for the other areas.

5. Limitations, Conclusions and Recommendations

5.1. Limitations

- The percentages of land cover components were visually estimated at only one point in time which might influence the results in terms of data precision.

- Field data collection dates were not corresponding with the dates of 2004 and 2008/2009 orthophotos.

- Few numbers of surveyed points in areas having natural and semi-natural land covers.

5.2. Conclusions

- The present study showed the importance of preliminary user-settings to generate land cover change maps through the prototype method.

- The study showed how the generated maps are sufficiently different concerning different choices of user-settings.

- The study successfully found the best choice of user-settings in order to produce more accurate land cover change maps which correctly represent the actual changes. The study emphasizes that when “threshold” was set as 1.5” and “period within the year” was chosen as “the whole year”. The study emphasizes that the “threshold” of “1.5” and “whole year” as “period within the year” with high agreement (85%) between simulated changes and observed changes are the best choice of preliminary user-settings in order to generate the most accurate land cover change map for the areas having natural and semi-natural land cover in Andalucia region.

5.3. Recommendations

- Use of newer orthophotos for field data collection and up-scaling process.

- Collect data in agricultural area in correct seasons, in order to learn more about inter-seasonal changes of different land cover types.

- Collect more data in the areas with the natural and semi-natural land cover.

- Explore other classification approaches for aerial photos which might lead to better results taking into consideration the complexity of different image objects.

- Redo the observed change estimation method for the areas with agricultural land covers as it was not possible with available data to validate this method for agricultural areas and study different user-settings.

- Do a follow up study in other areas, in order to find out the impact of user-settings on different areas.

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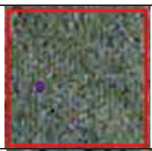
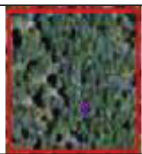
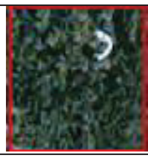
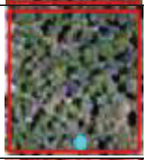
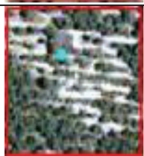
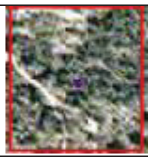
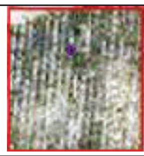
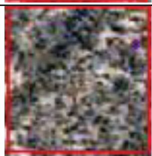
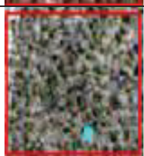
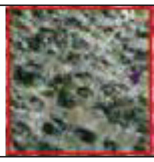
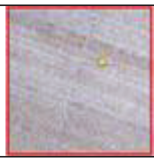
Appendices

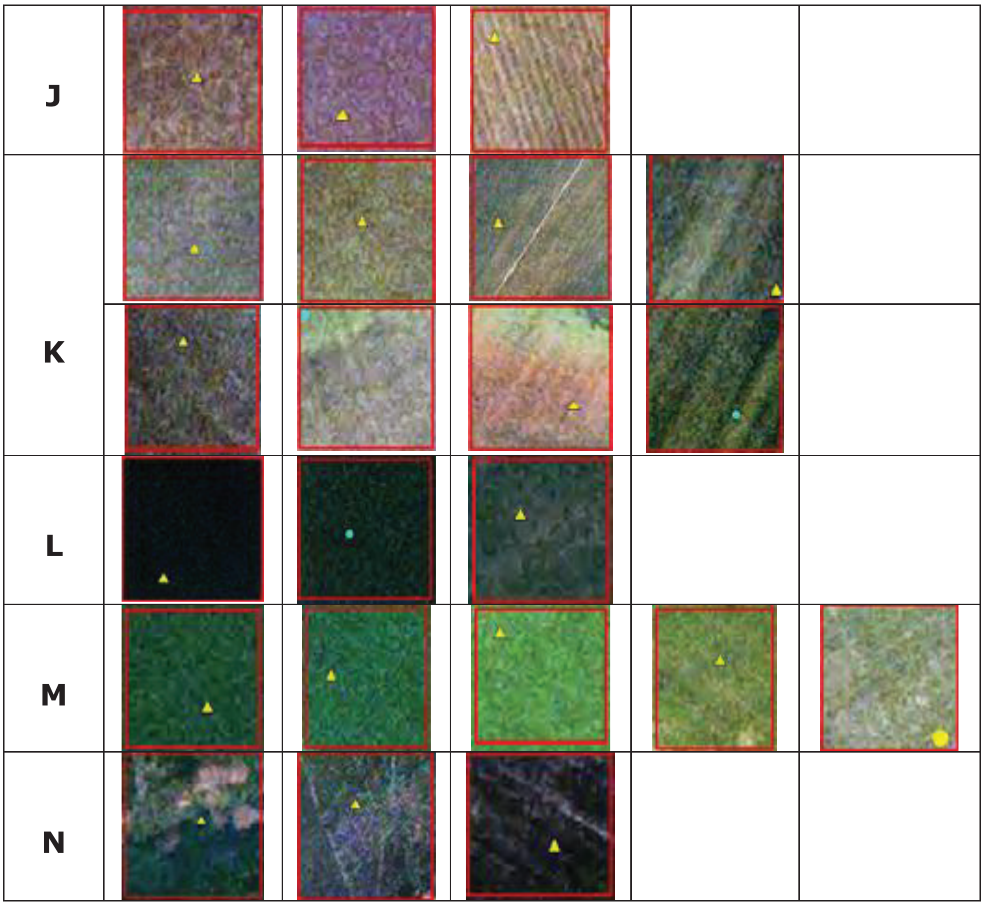
Appendix 1: Data sheet used for data collection

Date: **Sample ID:**

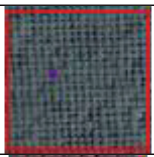
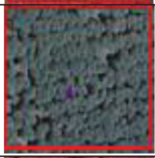
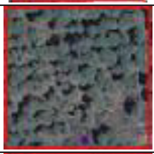
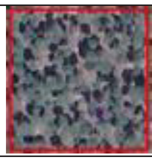
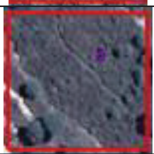
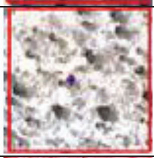
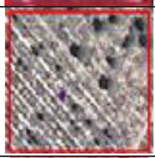
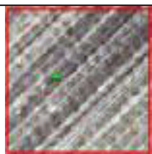
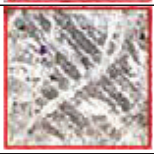
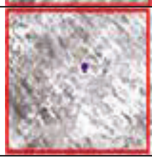
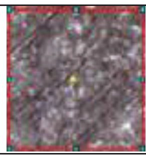
Photo No.	X	Y
Trees (%)	**Shrubs (%)**	**Grass/Herbs (%)**
Stones (%)	**Litter (%)**	**Bare Soil (%)**
Life form		**Change state**
Description		

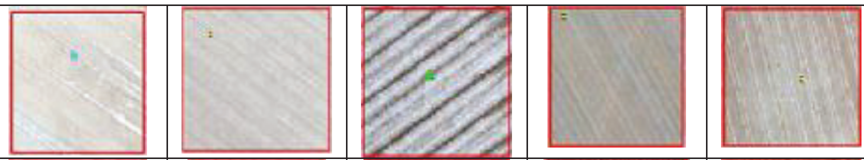
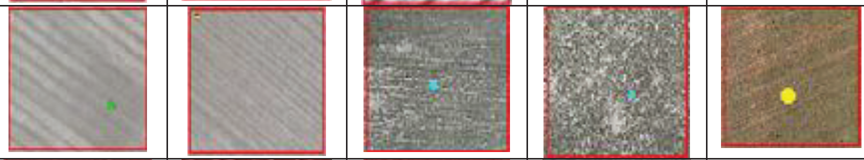
Appendix 2: Image object legend (2004)

Group					
A					
B					
C					
D					
E					
F					
G					
H					
I					


J
K
L
M
N

Appendix 3: Image object legend (2008/2009)

group					
A					
B					
C					
D					
E					
F					
G					
H					
I					

J	
K	
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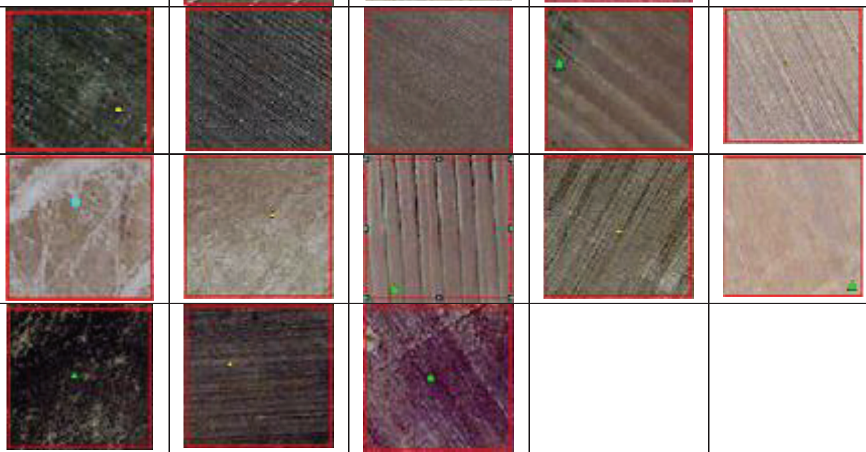
M	
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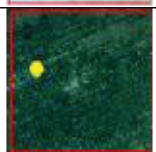
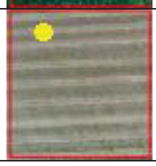
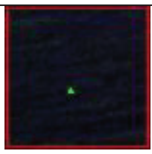
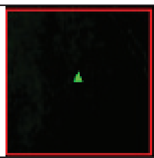
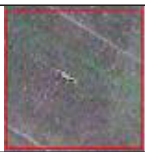
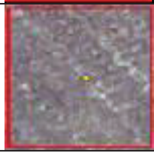
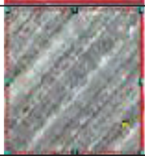
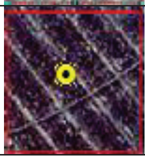
O	
P	

Q					
R					
S					
T					

Appendix 4: Regression analysis (60 Pixels with mixed land-cover)

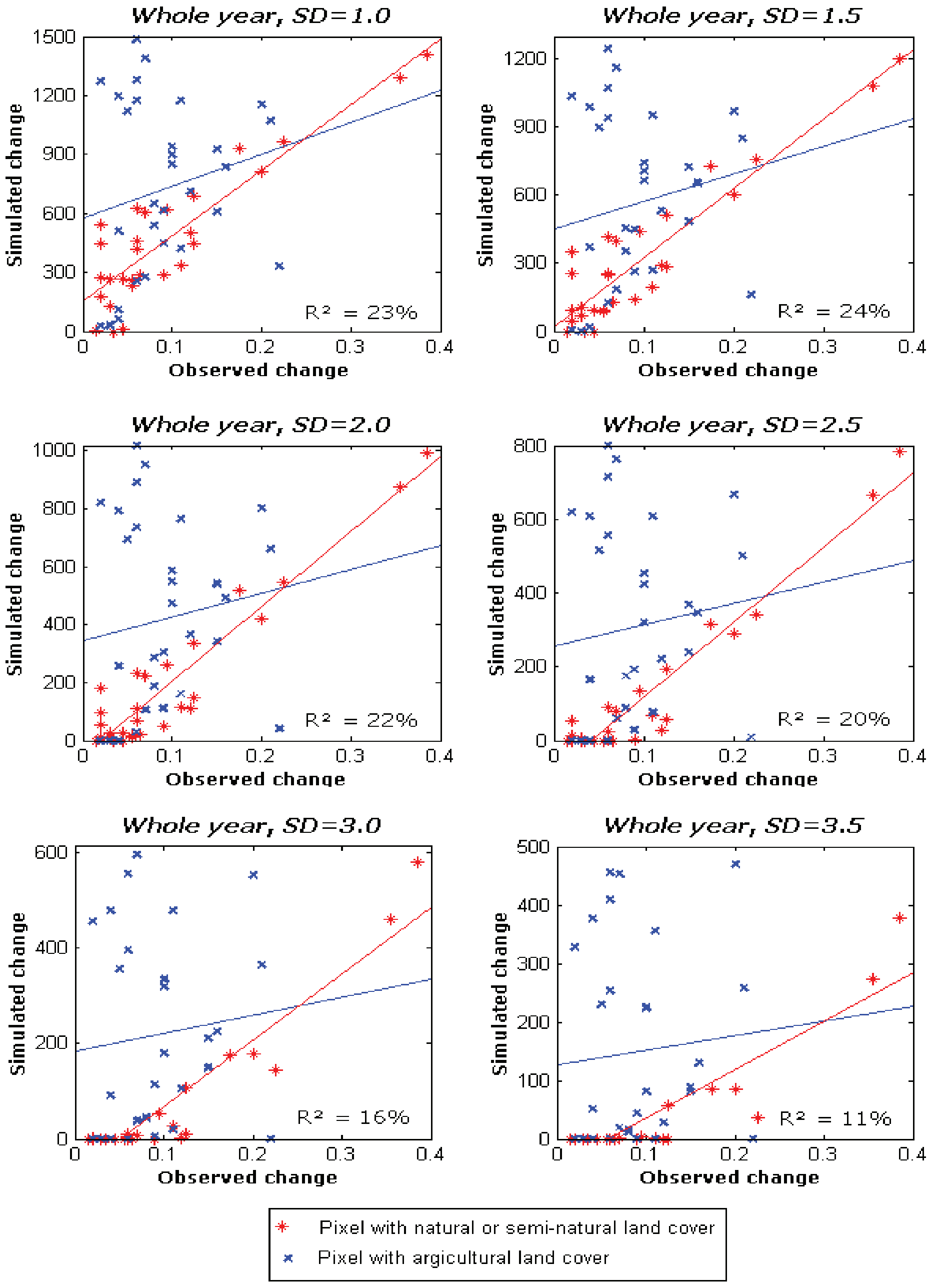


Figure 17: Simulated changes versus observed changes (2009 – whole year), Number of pixels: 60.

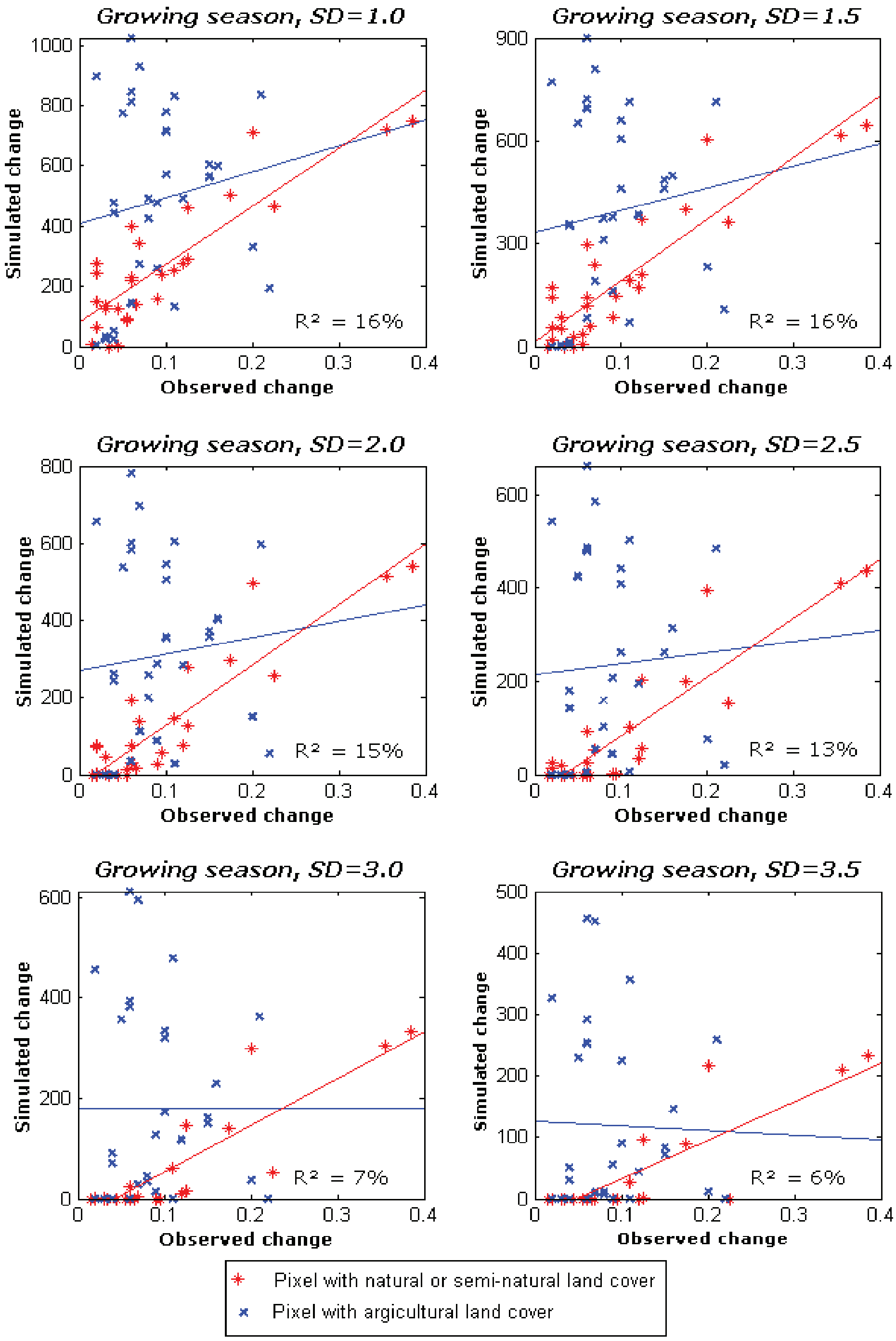


Figure 18: Simulated changes versus observed changes (2009 – growing season), Number of pixels: 60.