A novel approach of land cover change mapping using hyper temporal images

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A novel approach of land cover change mapping using hyper temporal images

by

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Abstract

Changes in the land cover affect the ecosystem condition and function. Use of vegetation index such as NDVI is the most common way to study the spatial and temporal trends in land cover dynamics. The issue of influence of phenology on land cover change detection is eradicated by the use of hyper temporal images. The study proposes to generate a novel approach of land cover change mapping based on hyper temporal image analysis and to verify it. The study was carried out in the Andalusia region of Spain. SPOT 10 day NDVI (Normalized Difference Vegetation Index) MVC (Maximum Value Composite) images from 2000 to 2009 were used. An algorithm was devised to detect decade wise anomalies at pixel level in the images of 2005 to 2009, using reference standard deviation (generated from 2000-2004 images). The algorithm further leads to interpretation calibration and reinterpretation of anomalies to obtain the final change map with cumulative weightages at pixel level. A total of 35 change pixels have been sampled in the field. Out of which 12 pixels were found completely change. Analysis of variance (ANOVA) was carried out on 7 pixels to ascertain significant or non significant change in a pixel. Six pixels out of 7 showed a significant change while 1 pixel showed a non-significant change. Confirmation of significant change in 18 out of 19 pixels emphasise the effectiveness of the novel approach of land cover change mapping based on hyper temporal image analysis.

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Keywords: Change detection, NDVI & hyper temporal images.

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1. Introduction

1.1. Background and significance

Change means being different or making something or someone different. It is an integral phenomenon of the dynamic world and has different gradients. Sometime, it is a very slow and gradual process which takes million of years whereas sometime it is an intermediate or very rapid process. The dynamics of both kind of change depends on natural as well as man-made factors. In respect to the natural environments, change could be found in climate, biophysical and geophysical parameters like vegetation, biodiversity, aquatic systems, land cover etc.

Detecting change is an important aspect of understanding the natural world and its dynamics. According to Singh (1989), "Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times." Quantitative approach of analyzing the temporal effects of change using multi temporal dataset is the basis of change detection.

Singh (1989) and Lu et al. (2004) illustrated a comprehensive review of various change detection techniques using remotely sensed data. Singh (1989) emphasised on the more precise geometric registration of satellite images to get a better change detection output. Emphasis was also on taking the account of various other factors like difference in atmospheric condition, sensor calibration, ground moisture condition, illumination while considering the difference in radiance values and actual change in land cover. Singh (1989) discussed various method of change detection like univariate image differencing, image regression, image ratioing, vegetation index differencing, principal component analysis, post-classification comparison, direct multi-date comparison, change vector analysis and background subtraction with a due consideration on their threshold boundaries of change and non-change. The change detection method was further categorised into more

organized categories by Lu et al. (2004) based on the techniques employed. The change detection categories were algebra, transformation, classification, advanced models, Geographical Information System approaches, visual analysis and other approaches. These categories have several sub categories within it.

As per Lu et al. (2004) most common change detection methods like image differencing, CVA (change vector analysis), PCA (Principal Component Analysis) and Post-classification comparison have been employed by several investigators. Muchoney and Haack (1994) worked on image differencing method to monitor the forest defoliation. CVA (Change Vector Analysis) was employed by Johnson and Kasischke (1998) as well as by Allen and Kupfer (2000) to study the land cover change and changes in spruce-fir forest respectively. These two methods use the two date images for change detection. While image differencing method subtracts two date images pixel by pixel for change detection, CVA describes direction and magnitude of change from the first to the second date respectively (Lu et al. 2004). Image differencing method described here are relatively easy to apply and interpret unlike change vector analysis which is relatively complex but a disadvantage of both of these methods is the selection of suitable image bands. Also, selecting an appropriate threshold to determine the change and no change status restricts the wider applicability of the method. In context of the present research, the method does not solve the purpose of determining and monitoring the change on a continuous basis.

Byrne et al. (1980) and Ingebritsen and Lyon (1985) studied land cover change detection using PCA. Study on change detection using post-classification comparison method was employed by several investigators like Miller et al. (1998), Foody (2001) who worked on land cover change, Munyati (2000) worked on wetland change and Ward (2000) worked on growth monitoring on urban areas. PCA and post-classification comparison method uses two or more dates of images. PCA implies correlation in multi-temporal data and highlights change information in new components whereas a post classification comparison separately classifies

images into thematic maps and then assesses the change (Lu et al. 2004). PCA reduces the redundancy between bands and its components reveals better information but acquiring suitable threshold as well as detailed change matrices are the major limiting factors. Though post-classification comparison produces a detailed change matrix but the requirement of appropriate training sample sets for classifying the multi date images is the limiting factor for this method. These two methods have a similar limitation in context of the present research of not having a sufficiently enough involvement of high temporal resolution data for continuous monitoring of change.

Besides using the above mentioned methods individually, several researchers have used a combination of two or more methods to improve the precision of change detection. Li and Yeh (1998) inferred that by using a combination of principal component analysis on stacked multi-temporal images and supervised classification one can minimize the error in effectively monitoring the land use change in Pearl River Delta. Image differencing method together with post-classification change detection method on the aerial photos of 1954 and SPOT XS of 1992 was used by Petit et al. (2001) to study the land cover change in Zambia. Combinations of methods provide better results in some cases (Gong, 1993) but are less common in practice due to its complexity.

Land cover is described as the visible features of the earth's surface which include vegetation, natural or man-made features at a specific time of observation (Campbell, 2006). This term is often been confused with land use. Land use is described on the basis of the use of land cover by humans (Campbell, 2006). Usually land use is defined in economic context such as agricultural, residential land.

Changes in the land cover are described as an important process, which affects the ecosystem condition and function. Turner et al. (2007) described land cover and land cover change as an important variable in major environmental issues. The phenological dynamics of terrestrial ecosystems reflects the variability and trends of

land cover over specified time intervals. Change in land cover has its impact on biodiversity (Jones et al. 2009), hydrology (Eshleman, 2004), geomorphology (Foulds and Macklin, 2006), global warming (McAlpine et al. 2009).

Usually, land cover changes are categorised in 'land cover conversion' and 'land cover modification' (Coppin et al. 2004). Coppin et al. (2004) described land cover conversion as "complete replacement of one cover type by another" whereas land cover modification was described as "more subtle changes that affect the character of land cover without changing its overall classification".

Based on the temporal characteristics, land cover change detection methods have been classified into 'bi-temporal' where change detection is assessed between two dates and 'temporal trajectory analysis' where change detection is assessed on timeprofile-based data with multi timescale (Coppin et al. 2004).

The use of vegetation indices in remotely sensed data is usually carried out for land cover monitoring (Budde et al. 2004). Digital brightness values are the basis of vegetation indices which attempt to measure biomass or vegetative vigour (Campbell, 2006). Healthy vegetation is designated by higher values of vegetation index. Simplest calculation of vegetation indices is based upon the ratio between two digital values from separate spectral bands (Campbell, 2006).

NDVI (Normalised Difference Vegetation Index) is the most common vegetation index used to study the spatial and temporal trends in vegetation dynamics (Beck et al. 2005). NDVI is an easily available product and it is also easy to calculate it. Several sensors like SPOT, MODIS, AVHRR has pre-processed NDVI data product. The availability and functionality of NDVI makes it a commonly used vegetation index. Baret and Guyot (1991) discussed about the correlation between NDVI and green leaf area index (LAI), green biomass and percent green vegetation cover. According to Zhang et al. (2003), vegetation phenology follows a relatively well defined temporal pattern (Figure1). Study of temporal dynamics of vegetation as

well as the temporal variation of land cover requires time series dataset which could provide repetitive coverage at very short intervals. This time-series dataset can help not only in the spatial analysis but it also contributes in analysis due to variation in time. The data with very fine temporal resolution (with 1 day sensor repeat time) is termed as hyper temporal data.



Figure 1. NDVI pattern along the time axis.

The status of land cover varies with time so it is important to monitor them on a regular basis. Sensors like, National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), Syste`me Probatoire de l'Observation de la Terre (SPOT) VEGETATION, Sea-Viewing Wide Field-of-View Sensor (SeaWIFS), Moderate-Resolution Imaging Spectrometer (MODIS), Along Track Scanning Radiometer (ATSR), etc have very fine temporal resolution and serves the purpose of monitoring. Hyper temporal images also eradicate the issue of influence of phenology on change detection (Coppin et al. 2004).

Zhan et al. (2002) used MODIS 250m data to monitor land cover change by developing decision tress for VCC (Vegetation Cover Conversion). Lunetta et al. (2006) also used multi-temporal MODIS NDVI data for land cover change detection by calculating total NDVI difference output data for change periods. Use of integrated post classification and temporal trajectory analysis was also used for land

cover change mapping (Ramoelo, 2007). de Bie et al. (2008) conducted studies on hyper temporal image analysis of crop mapping and multivariate change detection method over 10-days composites of SPOT-NDVI data. Nielsen (2008) worked on the outlier detection method using three dates of Landsat TM data of wetland for mapping change probability. Morisette & Khorram (2000) also worked on deriving a continuous probability-of-change map from statistical models using two dates of Landsat TM data.

Various methods of change detection, ranging from bi-temporal (Coppin and Bauer, 1995) to multi-temporal (Wilsons and Sader, 2002) image analysis, have been devised till now. Investigators have also worked on the combination of two or more than two methods to improve the change detection procedure (Li and Yeh, 1998; Petit et al. 2001). Although some studies (Zhan et al. 2002; Lunetta et al. 2006; Ramoelo, 2007; de Bie et al. 2008; Beltran, 2009) have been done on the high temporal frequency images for the generation of land cover and analysis of land cover change but none of them worked on the analysis of the commencement of change. The method proposed here works on algorithm which states about when the pixels start behaving as a change pixels within a specified time period. The change was defined in terms of variation in the NDVI values of land cover. The study also briefly illustrates about conversion and modification of image objects in land cover at pixel level. The method proposed in this research make use of continuous long term hyper temporal dataset for detecting anomalies associated with time to remove the influence of seasonality on land cover. The method also proposes to validate the pixel based on field data acquired, to assure the change status of the pixel.

1.2. Research problem

Many methods of change detection have been explored. Several investigators have worked on the time profiles of vegetation indices, which when departs from normal signifies the change event (Lambin and Strahler, 1994) while few have worked on method development for the creation of legend based on the data itself and analysis of with in class change evaluation (Beltran, 2009). Although there is no dearth of

literature and methods on land cover change detection but most of them are based on the use of limited time images and do not use regular seasonal interval or high temporal frequency images (Coppin and Bauer, 1995; Wilsons and Sader, 2002). There are methods that used the high temporal frequency data of a continuous long period for change detection (Ramoelo, 2007). However, the problem of tracking the beginning of change as well as its continuous monitoring of behaviour received little attention. Therefore, the most important aspect of change detection is to monitor the behaviour of change with time at pixel level.

The study attempts to utilize hyper temporal datasets to investigate the commencement of land cover change, its behaviour through the time and its verification at pixel level.

1.3. Research objective

To generate a novel approach of land cover change mapping based on hyper temporal image analysis and to verify it.

1.4. Research questions

Question1. How can hyper temporal data be used to generate by NDVI class, a Reference Profile?

Question2. How to detect anomalies present in a sub-sequent hyper temporal dataset and present them in a change map?

Question3. Does the change derived by algorithm at pixel level also corresponds to the change on ground?

1.5. Research hypotheses

Related to research question 3:

Ho \rightarrow There is no significant difference between change & non-change points in a pixel. (The change in the pixel is non-significant. Therefore, the change derived by algorithm at pixel level does not correspond to the change on ground.)

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\mu 1 = \mu 2
```

Ha \rightarrow There is significant difference between change & non-change points in a pixel. (The change in the pixel is significant. Therefore, the change derived by algorithm at pixel level also corresponds to the change on ground.)

 $\mu 1 \neq \mu 2$

where, μ 1: Mean of change field data points of all classes

 $\mu 2$: Mean of non-change field data points of all classes

1.6. Research approach

The study primarily consists of five steps. The approach of assessing the accuracy of land cover change is based on the flow diagram (Figure 3). The first step was pre processing of datasets, which was initially based upon de Bie et al. (2008). The Reference Standard Deviation by class was created in this step.

Second step was change detection modelling. In this step NDVI profile of every pixel (after eliminating anomaly due to external factor) was generated and was compared with Reference Standard Deviation by class to detect the anomalies. These anomalies were later analysed with respect to NDVI profile of every pixel to determine the change pixels. Weights were assigned to every change pixel based on the year of change identified.

Step three involved field work based upon the change pixel identified during step two. Data on change as well as non-change pixel was collected from the field. In step four, reinterpretation of anomaly data was done on the basis of new threshold generated using field data. The final change consists of change pixels identified using algorithm made in earlier steps.

The final and fifth step involved the validation of change pixels in the final change map. Based on validation results, recommendations were given to further improve the algorithm.

2. Materials and Method

2.1. Study Area

Andalusia is the autonomous community in southern Spain (Figure 2). It is the most populous region of Spain with 8,285,692 inhabitants in 2009. It is the second largest autonomous community in Spain with an area of about 87,268 km2. It consists of 8 provinces and 770 municipalities, with its capital as Seville. It is located between 36° and 38° 44' N in the warm temperate region. In general, it has Mediterranean climate with hot, dry summer and mild, rainy winter but the climate of Andalusia varies from dry desert in the east to the area of highest rainfall in Spain, in the west. The average temperature of Andalusia is about 16° C.



Figure 2. Map of study area, Andalusia, Spain.

The terrain of Andalusia is mainly dominated by moderate sized mountains with Sierra Morena as the prominent peak. Andalusia has typically Mediterranean vegetation, dominated by species like Holly Oak (*Quercus ilex*), Cork Oak (*Quercus suber*) and various pine and fir species. Olive (*Olia europaea*) and almonds (*Prunus*)

dulcis) are also very common. Agriculture is a very important component in the region having 67% of area covered by it. The major crops include wheat, maize, olives, oranges, sunflower and cotton.

2.2. Data used

Data used were SPOT4 and SPOT5 Vegetation (VGT) Sensor's 10-day MVC (Maximum Value Composite) NDVI-images (S10 product) at 1 km² resolution from 2000 to 2004 as reference dataset and from 2005 to 2009 for the generation of change maps. The images were obtained from <u>www.vgt.vito.be</u>. The SPOT-VEG spectral bands mentioned below were designed specifically to study vegetation cover and its temporal dynamics;

- Red 0.61 to 0.68 µm
- Near-infrared 0.78 to 0.89 µm
- Short-wave infrared 1.58 to 1.75 μm
- Blue band 0.43 to 0.47 μm, for atmospheric corrections.

The red and near-infrared bands are used by VITO for making daily and S10 Normalized Difference Vegetation Index (NDVI) composites.

Aerial orthophotos of 2004 along with SPOT were used to support the collection of data in the field for mapping and validation. Aerial ortho photos of 2007 were used for presentation of parts of result.

2.3. Software used

ERDAS Imagine 2010 and ENVI 4.7 were used for the image processing. Arc GIS 10 was used for data preparation, analysis and map composition. An Anomaly Detection Tool was used to detect the change pixel containing anomalies based on user specified thresholds and inputs. MS Word was used for documentation while MS Excel and SPSS were used for statistical analysis. Arcpad and Tom-Tom were used in the field for navigation and data collection.

2.4. Method

The step wise process of land cover change mapping is shown in figure 3. The whole process is categorized into 5 steps as mentioned below. However, the basic concept of change detection used in the study is described in the conceptual diagram (Figures 5, 6, 7 and 8)

- Pre-processing
- Change detection modelling
- Field data collection
- Reinterpretation of anomaly data
- Assessment of significant change

2.4.1. Pre-processing

Pre-processing is further divided into following steps

2.4.1.1. Stacking of data

The SPOT 10 day NDVI MVC images were stacked for the study area. The stacked NDVI data had two time periods. The first time period corresponds to the duration from January 2000 to December 2004 and had five stacked layers while the second time period corresponds to the duration from January 2005 to December 2009. Each layer corresponds to a year.

2.4.1.2. ISODATA clustering

This step initially followed the methodology described by de Bie et al. (2008). The NDVI dataset from January 2000 to December 2004 were processed using the Iterative Self-Organizing Data Analysis Technique (ISODATA) (Figure 6, Step 1). ISODATA is an unsupervised clustering procedure where minimum spectral distance technique is used to form clusters (Campbell, 2006). The NDVI dataset were classified using ISODATA technique with convergence threshold of 1 and maximum number of iterations as 50. The classification ran 90 times to define unsupervised classes maps having 10 to 100 classes each.

Divergence statistics expressed in separability values was used to select the best classified image. The divergence statistics employed the average and minimum separability values to assess the best classified NDVI map (Figure 6, Step 2). The average separability values explain the similarity among all the classes while the minimum separability explains about the similarity between the two most similar classes; both separability values should be high while the class number should remain limited. Based on these parameters best classified NDVI map was selected (Figure 6, Step 3).

2.4.1.3. Processing standard deviation data

The best classified NDVI map was used to generate the change map on pixel basis. A segment layer was prepared from the best classified NDVI map. It consists of all the segments of every class present in the best classified NDVI map. These segments were also considered as map units. Isolated single pixels were removed from the best classified NDVI map to eliminate the inherent abnormality which could occur due to presence of single pixel of a class in a different map unit. After the removal of single pixel the remaining best classified NDVI map was termed as mask layer. Out of the best classified NDVI map, standard deviation (SD) values were derived for each class at each decade, which was a total of 180 values (Figure 6, Step 4). These standard deviation values of five years for every class were then merged to a 1-year time profile (36 values). Thus, every class had a merged 1-year time profile standard deviation value generated out of five year (2000-2004) standard deviation values. This merged standard deviation was referred as Reference Standard Deviation by class (Figure 6, Step 5).



Figure 3. Flowchart of work process.

2.4.2. Change detection modelling

Change detection modelling is further divided into following steps.

2.4.2.1. Processing of SPOT NDVI (2005-2009)

The inputs generated (mask layer, segment layer and Reference Standard Deviation by class) from best classified NDVI map was then processed using the customized Anomaly Detection Tool.

The map units of best classified NDVI map (2000-2004) were also considered as the map units of SPOT NDVI dataset from January 2005 to December 2009 (Figure 7, Step 6). Mean was obtained for every single map unit in the SPOT NDVI dataset from January 2005 to December 2009 (Figure 7, Step 7). NDVI values of every pixel were also obtained within the same map unit (Figure 7, Step 8). The obtained mean was later subtracted from every pixel of same map unit on a decadal (every 10-day composite NDVI images) basis (Figure 7, Step 9). The process was repeated for every map unit in the dataset to obtain the difference values for every year from 2005 to 2009. The difference values generated out of above activity were treated in the absolute (positive) form.

2.4.2.2. Anomaly detection

The acquired absolute values of every pixel where then compared with the Reference Standard Deviation by class on a decadal basis. The comparison leads to the detection of anomaly in pixels in every respective map unit.

For every decade, if the absolute value of a pixel was outside the designated range of Reference Standard Deviation by class then it was considered as anomalous and assigned a value 1, where as if the value was within the designated range of Reference Standard Deviation by class then it was considered as non-anomalous and assigned a value 0 (Figure 7, Step 10).

2.4.2.3. Interpretation of time series anomaly data by pixel

The detection of specified number of anomalies leads to the identification of change pixel (Figure 8, Step 11). At first a user specified threshold of anomalies was decided. Based on it, if the duration of a single year or 36 decades contained anomalies more than a user specified threshold (greater than 75% anomalies per year

i.e. 0.75*36=27 anomalies/year at 1 standard deviation) then the pixel in that year was considered to have changed otherwise not. In every year change was investigated for every pixel. If any of the years from 2005 to 2009 was changed, then that pixel was considered to have change (Figure 8, Step 12). An example of the profile of change and non-change pixel is shown in figure 4.

The change pixels were assigned weights based on the year of change detected (Table 1). Pixels with recently detected change (e.g. year 2009) were assigned higher weights than pixels with earlier detected change (e.g. year 2005). Pixels with higher cumulative weightage were given higher importance in change detection assessment.



Figure 4. Change (a) and Non-Change (b) pixel.

The change pixels together constituted the preliminary change map with cumulative weightages indicating probability of change at pixel level.

Year	Weight	Cumulative Weightages
2005	1	$[\Sigma(\text{Change Pixels of } 2005 \times 1)] \div 15$
2006	2	$[\Sigma(\text{Change Pixels of } 2006 \times 2)] \div 15$
2007	3	$[\Sigma(\text{Change Pixels of } 2007 \times 3)] \div 15$
2008	4	$[\Sigma(\text{Change Pixels of } 2008 \times 4)] \div 15$
2009	5	$[\Sigma(\text{Change Pixels of } 2009 \times 5)] \div 15$

Table 1. Cumulative weightages of change pixels based on year of change detected.

2.4.3. Field data collection

Prior to field data collection literature review, pre processing of data and preliminary change map preparation was done. The data was collected in duration of 20 days during mid September 2010 in Andalusia, Spain. Best classified NDVI map and preliminary change map along with aerial orthophotos of the corresponding areas were used for collecting data on land cover. Pixels of both change as well as non change were selected and a systematic random sampling was followed on the sampling sites. The sample unit was taken as 1km² to correspond with SPOT data's pixel size. In every sampled pixel all the image objects were surveyed. Data was collected on vegetated as well as non-vegetated aspects of every image object (Appendix I).

A total of 35 change pixels were surveyed in the field. Surveyed pixels were selected based on the weights assigned to them. Pixels of higher weights were given preference in survey. Other criterion of selection was based on the accessibility of the pixel. Similarly some pixels of non-change were also visited and similar data was collected from these pixels.

2.4.4. Reinterpretation of anomaly data

With the help of data collected from field reinterpretation of anomaly data was done to generate the final change map.

2.4.4.1. Calibration and model result interpretation

Data from the field survey facilitated the identification of those change pixels in which all the surveyed points indicated the change. Thus based on the field data, completely changed pixels were identified. Some of these completely changed pixels were used to decide a new threshold based on field data. Iterations of interchanging, both the threshold as well as the standard deviation was carried out. This resulted in a derivation of specific standard deviation of 1.1 and a threshold of 66.66% of









overall anomalies (0.66*36=24 anomalies) above which a pixel in a specified year was flagged as a change pixel (Figure 8, Step 11).

Based on the newly derived threshold, new inputs were generated, which included new mask and segment layer from the best classified NDVI map and a new Reference Standard Deviation by class (at 1.1 SD) which was then processed using the customized Anomaly Detection Tool to generate the final change map with cumulative weightages indicating probability of change at pixel level

2.4.5. Assessment of significant change

Some of the resultant change pixels from the final change map were used to test the significant change. The change pixels were validated using the field data points. Aerial photos of 2004 for the whole Andalusia region were available. After analysing the field data of change pixels, 12 pixels were found to have all the surveyed points indicating change on the ground. These pixels were considered as completely changed pixels. These pixels were not considered further to assess the significant change.

2.4.5.1. Verification of pixel using ANOVA test

To analyse the significant change in the change pixels, those change pixels were given consideration which had both change as well as non-change points observed in the field. A total of seven such change pixels were selected and verified to assess the significant change in the change pixels. These seven pixels were randomly selected from the study area. Legend was made for every pixel. The legend was made using observed non-change field data points which were present both within and outside the change pixel within the same map unit. This legend facilitated the interpretation of image objects in the 2004 aerial photos which were later digitized. The field data points of 2010 and interpreted image objects in 2004 aerial photo of the change pixel was together used to do a two way ANOVA test to examine the significant difference between the change and non-change points in the corresponding change pixel. A schematic representation of the selection of field data points and image

objects in a pixel for the test of significant change using ANOVA is given in the following diagram (Figure 9).

Figure 9. A schematic representation of field data points and image objects for significant change analysis.

2.4.5.2. Pixel with significant and non-significant change

Two way ANOVA test proved the significant and non-significant change in the pixels. Pixel which had significant difference between change and non-change points were considered as pixel with significant change while pixels which does not have significant difference between change and non-change point were considered as pixel with non-significant change.
3. Results

3.1. ISODATA clustering

The ISODATA technique was used on the SPOT NDVI data (January 2000 to December 2004). The data was classified using 50 iterations with a convergence threshold of 1. Classified maps having 10 to 100 classes were generated (90 ISODATA runs). The values of average and minimum separability were assessed using Erdas signature evaluater (Leica Geosystems, 2005). Based on average separability and minimum separability values, the best number of class was selected. It is evident from the figure 10 that the peak of average separability as well as the peak of minimum separability follows a similar trend at class 46.



Figure 10. Divergence statistics (Avg & Min) to identify the best number of classes.

Thus, the classified NDVI map with 46 classes was selected as the best classified NDVI map (Figure 11 to 15) which was further used for the anticipated change detection modelling.





Figure 12. NDVI legends (1 – 11) from best classified NDVI map (46 classes).



Figure 13. NDVI legends (12 – 22) from best classified NDVI map (46 classes).



Figure 14. NDVI legends (23 – 33) from best classified NDVI map (46 classes).



Figure 15. NDVI legends (34 – 46) from best classified NDVI map (46 classes).

The best classified NDVI map with 46 classes (2000-2004) was used to generate the reference standard deviation by class.

3.2. Change detection modelling & reinterpretation of anomaly data

The best classified NDVI map with 46 classes was used to create mask and segment layer. These layers together with the Reference Standard Deviation by class were processed using customized anomaly detection tool. The tool generated out the five different layers where each layer corresponds to a year ranging from 2005 to 2009. Each layer signifies changes occurred at pixel level on the basis of algorithm formulated in the present method. These five layers combined together to constitute the preliminary change map. The preliminary change map was then calibrated using the field data to redefine the threshold. Based on new threshold the anomaly data was reinterpreted and weightages were assigned based on recent detected anomalies which lead to the generation of final change map with threshold data indicating probability of change at pixel level (Figure 16).



3.3. Assessment of significant change

Seven random pixels selected from the final change map. Every map unit in which the concerned pixel lies was selected for legend generation. The legends created for every pixel were based on the observed non-change field data points both within and outside the change pixel within the same map unit. The significant change in these pixels was verified using two way ANOVA test.

3.3.1. Verification of pixel using ANOVA test

ANOVA test was conducted on the 7 selected change pixels. The details of ANOVA test for every pixel is described as follows.

Pixel 1

The image objects are mainly dominated by pine and eucalyptus vegetation along with shrub and herb layers. Patches of eucalyptus plantation and open areas were also found in the pixel. The legend of this pixel based on aerial orthophotos and visual assessment in the field are as follows:

Image object A: composed of approximately 82% of trees (mainly pine and oak trees), followed by approximately 15% grass/herb and 12% shrub. Image object 'A' occupied 18% area of the pixel 1.

Image object B: composed of approximately 57% of shrub followed by approximately 20% grass/herb. Image object 'B' occupied 28% area of the pixel 1.

Image object C: composed of approximately 62% of trees (mainly pine trees) followed by approximately 22% shrub. Image object 'C' occupied 27% area of the pixel 1.

Image object D: composed of approximately 32% tress (mainly eucalyptus) followed by approximately 24% open area and 20% grass. Image object 'D' occupied 13% area of the pixel 1.

Image object E: composed of approximately 27% trees (eucalyptus) followed by approximately 25% open area and 17% litter. Image object 'E' occupied 14% area of the pixel 1.

Based on the legend of this pixel the image object were digitized and classified into respective groups (Figure 17). A total of 9 out of 13 were change field data points sampled within the pixel and an ANOVA test was conducted using these points. The result of ANOVA test showed a *p*-value of 0.034.



Figure 17. Digitized and classified change pixel 1 with field data points.



This pixel had visible of signs of change when this area was visited in 2010. Pictures below indicate some of the visible sign of change observed in the pixel. (Figure 18)

Figure 18. Images showing visible signs of change in pixel 1.

The NDVI profile of pixel 10f the duration 2000-2004 and 2005-2009 showed the following trend (Figure 19).



Figure 19. NDVI profile of pixel 1 between 2000-2004 & 2005-2009.

Pixel 2

The image objects of this pixel are mainly dominated by pine trees and woody shrubs. High density of trees is present all over the pixel. The legend of this pixel based on aerial orthophotos and visual assessment in the field are as follows:

Image object A: composed of approximately 75% trees (mainly pine) followed by approximately 18% litter. Image object 'A' occupied 43.64% area of the pixel 2.

Image object B: composed of approximately 25% shrub and 30% herbs respectively. Image object 'B' occupied 4.80% area of the pixel 2.

Image object C: composed of approximately 45% shrub and 25% herb respectively. Image object 'C' occupied 12.20% area of the pixel 2.

Image object D: composed of approximately 45% trees (mainly of pine and eucalyptus) followed by approximately 30% shrubs. Image object 'D' occupied 29.22% area of the pixel 2.

Image object E: composed approximately of 43% open area followed by approximately 30% stones. Image object 'E' occupied 10.14% area of the pixel 2.

As per above mentioned legend, the image objects in the pixels were digitized. A visual as well as the details from the field data lead to the classification of this pixel (Figure 20). An ANOVA test was conducted using 10 change and 4 non-change field data points sampled within the pixel to test the significant change in it. The result of ANOAV test showed a *p*-value of 0.235.



Figure 20. Digitized and classified change pixel 2 with field data points.

The pixel had few visible signs of manmade changes which is shown in the below picture (Figure 21).



Figure 21. Sign of manmade change; a fire line along the hill slope.

The trend of NDVI profile of pixel 2 of the duration 2000-2004 and 2005-2009 is shown below (Figure 22).



Figure 22. NDVI profile of pixel 2 between 2000-2004 & 2005-2009.

Pixel 3

Image objects of this pixel are dominated by shrubs along with young eucalyptus plantation. Patches of young eucalyptus plantation as well as cut logs of eucalyptus was visible in the area. The legend of this pixel based on aerial orthophotos and visual assessment in the field are as follows:

Image object A: composed of approximately 80% shrub dominated areas followed by approximately 10% grass/herb. Image object 'A' occupied 15.44% area of the pixel 3.

Image object B: composed of approximately 36% open areas followed by approximately 21% grass/herb. Logged eucalyptus remains were evident in the area along with few young eucalyptus plantations. Image object 'B' occupied 41.65% area of the pixel 3.

Image object C: composed of approximately 36% open area followed by approximately 17% litters and 15% stones. Man-made terraces on the soil as well as few young eucalyptus plantations were also present in the area. Image object 'C' occupied 11.28% area of the pixel 3.

Image object D: composed of approximately 37% and 36% of shrub and herb/grass on the slopes. Few signs of fire and logging were also present here. Image object 'D' occupied 31.63% area of the pixel 3.

With the help of above mentioned legend along with the visual approach and details from the field data, the image objects in the pixels were digitized and classified (Figure 23). An ANOVA test was conducted using 13 change and 1 non-change field data point sampled within the pixel to test the significant change. The result of ANOVA test showed a *p*-value of 0.047.



Figure 23. Digitized and classified change pixel 3 with field data points.

The pixel when visited in the field had visible signs of change both in terms of logging as well as young eucalyptus plantations (Figure 24).



Figure 24. Images showing visible signs of change; remains of logging and new plantation of eucalyptus.

The trend of NDVI profile of pixel 3 of the duration 2000-2004 and 2005-2009 is shown in the figure 25.



Figure 25. NDVI profile of pixel 3 between 2000-2004 & 2005-2009.

Pixel 4

This pixel lies in a part of a small residential area called El Toyo in Almeria. The major image objects found here were residential areas, roads, open areas and golf course. The legend of this pixel is as follows:

Image object A: composed of approximately 45% and 37% grass/herb and open areas respectively. This area was mainly non-used public land. Image object 'A' occupied 61% area of the pixel 4.

Image object B: composed of approximately 55% and 44% built-up, roads and open areas respectively. Image object 'B' occupied 9.98% area of the pixel 4.

Image object C: composed of approximately 57% and 17% open and shrub respectively. Image object 'C' occupied 3.52% area of the pixel 4.

Image object D: composed of approximately 94% open areas. Image object 'D' occupied 25.50% area of the pixel 4.

The image objects of pixels were digitized and classified using legend described above (Figure 26). An ANOVA test was conducted using 7 change and 1 nonchange field data point sampled within the pixel.

The result of ANOVA test showed a *p*-value of 0.013.



Figure 26. Digitized and classified change pixel 4 with field data points.

The area had some remarkable signs of change e.g. golf course was developed in due course of time out of scrub land. Also the residential areas were fully developed to what it was in 2004. Following figure shows some depiction of the area (Figure 27).



Figure 27. Images showing areas of pixel 4; newly developed residential area & golf course.

The trend of NDVI profile of pixel 4 of the duration 2000-2004 and 2005-2009 is showed in figure 28.



Figure 28. NDVI profile of pixel 4 between 2000-2004 & 2005-2009.

Pixel 5

Pixel 5 was situated in the agricultural zone. The main composition of pixel is the plastic green houses made for growing vegetables or other plants. Along with plastic greenhouses, open areas with grasses were also abundant. The legend of this pixel is as follows:

Image object A: composed of approximately 10% olive plantations but it is mainly dominated by approximately 35% shrub. Image object 'A' occupied 3.02% area of the pixel 5.

Legend B: composed of approximately 46% herb/grass followed by approximately 37% open area. Image object 'B' occupied 39.74% area of the pixel 5.

Image object C: composed of approximately 95% open areas. Image object 'C' occupied 15.41% area of the pixel 5.

Image object D: consists of plastic green houses. Image object 'D' occupied 41.83% area of the pixel 5.

The above mentioned legend was used to digitize and classify the change pixel (Figure 29). An ANOVA was conducted using 13 change and 3 non-change field data points sampled within the pixel to test the significant change in it.

The result of ANOVA test showed a *p*-value of 0.030.





The pixel has some sign of changes mainly in the form of some new development of plastic green houses in place of open areas. The plastic green houses were abundant in whole area (Figure 30).



Figure 30. Image showing abundant plastic green houses in pixel 5; mainly used for agro-commercial purposes.

The trend of NDVI profile of pixel 5 of the duration 2000-2004 and 2005-2009 is showed in the following figure 31.



Figure 31. NDVI profile of pixel 5 between 2000-2004 & 2005-2009.

Pixel 6

This pixel had citrus plantations as dominant feature. The trees were fully grown and commercial harvesting was being practiced here. The plantation was among small hillocks. The legend of this pixel is as follows:

Image object A: composed of approximately 47% and 40% open area and grass/herb respectively, on hillocks. Image object 'A' occupied 8.16% area of the pixel 6.

Image object B: consists of approximately 45% and 40% open areas and grass/herb respectively but on flat areas. Image object 'B' occupied 20.18% area of the pixel 6. **Image object C**: composed of young citrus plantation. Image object 'C' occupied 0.36% area of the pixel 6.

Image object D: composed of approximately 67% mature citrus plantation followed by approximately 17% open land. Image object 'D' occupied 71.30% area of the pixel 6.

Details of this legend were used to digitize and classify the image objects in the change pixel (Figure 32). An ANOVA test was conducted using 17 change and 1 non-change field data points sampled within the pixel to test the significant change in it.

The result of ANOVA test showed a *p*-value of 0.028.



Figure 32. Digitized and classified change pixel 6 with field data points.

The pixel showed signs of changes in terms growth of citrus plantation. The trees were mature to what it was in 2004, which signifies an increased NDVI value. Image of the pixel are shown below (Figure 33).



Figure 33. Image showing mature citrus plantation in pixel 6.

The trend of NDVI profile of pixel 6 of the duration 2000-2004 and 2005-2009 is showed in the figure 34.



Figure 34. NDVI profile of pixel 6 between 2000-2004 & 2005-2009.

Pixel 7

Image objects of this pixel are mainly composed of young and mature citrus plantation. The legend of this pixel is as follows:

Image object A: composed of approximately 47% and 40% grass/herb and open land on hillocks slope respectively. . Image object 'A' occupied 24.60% area of the pixel 7.

Image object B: composed of approximately 45% and 40% grass/herb and open land respectively but present on flat areas. Image object 'B' occupied 5.67% area of the pixel 7.

Image object C: composed of young citrus plantation. Image object 'C' occupied 37.89% area of the pixel 7.

Image object D composed of approximately 67% mature citrus plantation followed by approximately 17% open land. Image object 'D' occupied 31.84% area of the pixel 7.

The legend was used to digitize and classify the pixel (Figure 35). An ANOVA test was conducted using 18 change and 3 non-change field data points sampled within the pixel to test significant change in it.

The result of ANOVA test showed a *p*-value of 0.035.



Figure 35. Digitized and classified change pixel 7 with field data points.

Image objects of this pixel showed signs of changes in terms of different growth level of citrus plantation. Image of young citrus plantations is shown below (Figure 36).



Figure 36. Image showing young citrus plantation in the pixel 7.

The trend of NDVI profile of pixel 7 of the duration 2000-2004 and 2005-2009 is showed in the figure 37.



Figure 37. NDVI profile of pixel 7 between 2000-2004 & 2005-2009.

The pixel details of some of the completely changed pixels are described in the Appendix II.

3.3.2. Pixels with significant and non-significant change

The table (Table 2) below shows the threshold of change generated by the algorithm, which explains about threshold of change occurred due to number of detected anomalies for a pixel. The table also shows *p*-values derived using ANOVA which explains about the significant and non-significant change status of a pixel.

	Threshold of change generated by the algorithm	P-value derived using ANOVA	Change Status of pixel based on P-value
Pixel 1	34	0.034	Significant Change
Pixel 2	31	0.235	Non significant change
Pixel 3	31	0.047	Significant Change
Pixel 4	36	0.013	Significant Change
Pixel 5	33	0.030	Significant Change
Pixel 6	36	0.028	Significant Change
Pixel 7	36	0.035	Significant Change

Table 2. Table showing change status of verified pixels.

4. Discussion

4.1. ISODATA clustering

The present study initially follows de Bie et al. (2008) in using the hyper temporal dataset (SPOT NDVI data) for ISODATA clustering to generate land cover map. Campbell (2006) described ISODATA technique as unsupervised clustering procedure which uses minimum spectral distance technique to form clusters. Using divergence statistics the NDVI map with 46 classes was selected as the best classification for data from 2000 to 2004. Swain and Davis (1978) also illustrated the use of maximum average divergence to select the signatures for classification. Recent study by Khan et al. (2010) also revealed the effectiveness of using divergence statistics and overall method. The best number of classes derived using clusters of spectral signature portrays the general variability in the land cover in an area. These 46 classes were later considered as segments with a purpose to take into account the local variability and changes within class. The mean of NDVI map with 46 classes and its standard deviation was used as Reference Standard Deviation by class. This made a base for onward change detection method.

4.2. Change detection modelling & reinterpretation of anomaly data

The role of hyper temporal data in detecting change in land cover has been investigated by several investigators (Zhan et al. 2002; Lunetta et al. 2006; Ramoelo, 2007; de Bie et al. 2008; Beltran, 2009). Correlation of hyper temporal data with green plant biomass makes it highly appropriate to study the changes occurring in the land cover or vegetation. Beck et al. (2005) stated NDVI as the most common vegetation index to study the temporal and spatial trend of vegetation dynamics. In the present study, fluctuations in the NDVI values at a defined threshold have been used to detect changes in the land cover.

An approach of identification of change pixels based upon its deviation from certain measure of central tendency of every pixel in its class is the basis of the algorithm employed in the study. Nielson (2008) also supported a similar approach in his study. In the study Reference Standard Deviation by class, was described as the central tendency. Deviation from which indicated the anomaly per decades for every pixel. At first, the user defined threshold of change was used in the study which was later calibrated using field data. The study reinterpreted the change detection and flagged those pixels as change that crossed the threshold of calibrated reference standard deviation of 1.1 and 24 anomalies per year. In addition to this, the effectiveness of the change detection also lied in the detection of the year of change commencement. The research shows promising results in explaining the use of detected anomalies present in NDVI of land cover for the identification of change pixels. These change pixels together constitute the change map. The land cover changes found in the pixels are attributed to the variation in the NDVI values and are mainly due to man-made activities like logging, plantation, establishment of new infrastructure etc. which was verified from field.

4.3. Assessment of significant change

In the study, a total of 35 change pixels were sampled in the field, out of which 12 pixels were found to be completely changed pixels. Other 7 pixels selected had both change and non change points. They were further checked with ANOVA for significant change assessment.

The result of pixel 1 showed a *p-value* less than 0.05. Thus the null hypothesis was rejected and a significant difference was observed between change & non-change points. It was supported by the NDVI profile of the pixel. The profile showed an increase in the NDVI value of 2005- 2009 from NDVI values of 2000-2004. The reason for the change in NDVI profile could be attributed to visible signs of change observed in the field such as burnt logs and patches of eucalyptus plantation. These types of changes considerably vary the NDVI values of the land cover.

The result of pixel 2 showed a *p-value* greater than 0.05. Thus the null hypothesis was accepted and a non-significant difference was observed between change and non-change points. Although the NDVI profile showed a slight variation between NDVI values of 2005- 2009 from NDVI values of 2000-2004 but not much visible signs of changes were observed in the field except for few man-made changes.

The result of pixel 3 showed a *p-value* less than 0.05. Thus the null hypothesis was rejected and a significant difference was observed between change & non-change points. The NDVI profiles of this pixel showed an increase in the NDVI value of 2005-2009 from the NDVI values of 2000-2004. This could be explained in accordance with the ground data where huge eucalyptus plantation was observed.

Pixel 4 has a *p-value* less than 0.05. Thus the null hypothesis was rejected and a significant difference was observed between change & non-change points. The difference between NDVI profiles of 2000-2004 and 2005-2009 is considerably high. NDVI values of 2005-2009 were higher than NDVI values of 2000-2004. The pixel falls in a residential area which is newly developed and its NDVI value increases mainly in terms of plantation for aesthetic purpose along the roads and houses as well as creation of a new golf course in the area.

The result of pixel 5 also showed a *p-value* less than 0.05. Thus the null hypothesis was rejected and a significant difference was observed between change & non-change points. The NDVI values of 2000-2004 profile showed a decreasing trend which could be due to increase of plastic green houses in the region. Later the NDVI values of 2005-2009 profile showed an increasing trend which became nearly equivalent to 2000-2004 profile.

Both pixel 6 and pixel 7 showed a *p*-value less than 0.05. Thus the null hypothesis was rejected and a significant difference was observed between change & non-change points for both the pixels. The NDVI profiles of both the duration (2000-2004 and 2005-2009) shows a remarkable difference. In both the pixels the NDVI

values of 2005-2009 are considerably higher than the NDVI values of 2000-2004. Though the values were higher but it followed the same temporal trend. The possible reason might be the citrus plantations. In pixel 5, the citrus plantation was more mature during the field visit than what it was during 2000-2004 as observed on aerial orthophotos. On a similar note pixel 7 had a mix of young and mature citrus plantations indicating a higher NDVI.

The study defined the change in terms of variation in NDVI. Changes in land cover leads to changes in their respective NDVI values. The study took two aspects of change into consideration. First, aspect addresses change of one cover type into another cover type. It is evident in pixel 4 of result section 3.3.1 that a golf course has been created in the area out of scrub land. Second aspect addresses the modification in a class itself. It is evident from the study of pixel 6 of result section 3.3.1 that the citrus plantation was more mature during the field visit than what it was during 2000-2004. Coppin et al. (2004) also discussed the two categories land cover changes as 'land cover conversion' and 'land cover modification'.

Six pixels out of 7 showed a significant change while 1 pixel showed a nonsignificant change. The positive relationship of change derived by algorithm at pixel level and the change on the ground was validated by 6 pixels (confirmed by ANOVA test) and 12 completely changed pixels. Confirmation of significant change of 18 out of 19 pixels emphasise the effectiveness of the novel approach of land cover change mapping based on hyper temporal image analysis.

The other method for validation of algorithm would have been achieved by the help of aerial orthophotos or high resolution imagery. However, the method was not used in the study because of unavailability of recent aerial orthophotos or high resolution imagery. In this method, the change status of pixels would have been validated by means of percent land cover derived by digitizing from the aerial orthophotos or high resolution imagery and comparing it with vegetation indices (NDVI) values acquired from the hyper temporal satellite image. Purevdorj et al. (1998) also

confirmed the use of digitized colour photo for percent vegetation cover and vegetation indices derived from spectral reflectance of various vegetation cover to derive a relationship between them.

As per present research questions the algorithm works satisfactorily but it could be improved further to answer some more aspects of change. For example an improvement in the algorithm for the future work could be incorporated through the analysis of quantification of probability of change in the pixel. If the sum of values (difference value) between the upper limit of threshold and change pixel for every year is considered then an approach towards quantification of probability of change could be generated (Figure 38) in addition to the identification of pixels with cumulative weightages indicating probability of change. The quantification approach could lead the algorithm towards a more meaningful interpretation of change.



Figure 38 Depiction of method for quantification of probability of change.

5. Limitations, Conclusions and Recommendations

5.1. Limitations

- 1 km spatial resolution of SPOT pixel was assumed to be of sufficient resolution to adequately detect the change in the Andalusia's landscape.

- It was assumed that NDVI classes were equivalent to map units.

- It was assumed that 5 year stack of SPOT NDVI data, used for making Reference Standard Deviation by class, had sufficient time period to be used for change detection.

5.2. Conclusion

The present study successfully answers the process of generation of reference profile using hyper temporal data which was used as a threshold reference to detect the anomalies present in NDVI of land cover. The study proved to be effective in deriving the change map out of anomalies using the change detection modelling. The study also verified the change derived by algorithm at pixel level in accordance to the change on ground. Eighteen out of 19 pixels were confirmed to be significantly changed thus, proving the authenticity of the algorithm. Therefore it can be concluded that the study revealed the effectiveness of the use of hyper temporal NDVI datasets and change detection algorithm in detecting the change at pixel level and retaining the approach of continuously monitoring the behaviour of pixel with time.

5.3. Recommendation

The present method identifies the change pixel and assigns cumulative weightages thus indicating the probability of change at pixel level but it does not consider the

quantitative approach of probability of change at pixel level. A further research on the assessment of quantitative values will help in obtaining the amount of probability of change from the hotspots of change identified in the present study.

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Appendix I: Data sheet used for field data collection

Date:		
Sample No		
X:	Y:	
Life Form:		
Tree (%)	Shrub (%)	_ Herb/Grass (%)
Stone (%)	Litter (%)	_Soil (%)
Water (%)	Waste (%)	_ Construction (%)
Agriculture (%)		
Change Pixel – Y/N		
Change		
Land Cover – Y/N	Land Use – Y/N	
Remarks:		

Appendix II: Few example of completely change pixel

Pixel A: Six change pixels were completely occupied by newly developed solar power plant, which started building in 2007 and was operational in 2010. The development is also quite evident in the NDVI profile of one of the pixel.

Ortho Photo



2004 (Empty pixel-Agricultural field)

Ortho Photo



2007 (Solar plant construction started)

ASTER Image



2010 (Solar plant construction complete)



NDVI profile varies from Reference SD from 2007 onwards - indicating change





Images from the field survey showing established solar plant

Pixel B: Change was visible in the field mainly in the form of remains of logged trees and new eucalyptus plantations. Logging was done after 2004 and was quite evident in 2007. After 2007 new plantations was done in the area. These changes are visible in the NDVI profile of the pixel also.

Ortho Photo



2004 (Eucalyptus trees)

Ortho Photo



2007 (Logged eucalyptus trees)





2010 (New eucalyptus plantations)



NDVI profile varies from Reference SD from 2007 onwards - indicating change



Images from the field survey showing remains of logged trees and new plantations