# LAND COVER AND LAND USE CHANGE DETECTION AND ANALYSES IN PLOVDIV, BULGARIA, BETWEEN 1986 AND 2000

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## ABSTRACT

This paper compares three remote sensing techniques to monitor land-cover change in Plovdiv County, Bulgaria (1986-2000) using multitemporal Landsat TM data. Following the fall of dictatorship in 1989, Bulgaria experienced major political and economic changes, not accompanied by the implementation of necessary instruments for managing land-use transitions. As a result, the country experienced rapid and widespread land-cover conversions- the extent of which is still unknown. The context of the study is based on three major issues in remote sensing science: 1) Unsupervised classification algorithms are currently under-utilized in land-cover applications; 2) Many developing countries, such as Bulgaria, are data-poor and the main information source for proper land management and monitoring are non-spatial summary reports; 3) A lack of reliable ground reference data in these countries demands the development of alternative methodologies to address this paucity.

Supervised and unsupervised classifications were used to map land-cover in 1986 and 2000 and post-classification comparison of map products produced maps of land- cover conversion. To assess land cover modifications, change vector analysis was then used to produce images of change direction and magnitude between the two dates based on two Kauth Thomas transformation features: brightness and greenness. Landscape pattern metrics were subsequently used to determine the status and trends in the condition of land-cover change process.

The results indicate that there was a significant increase in urban areas and decrease in agriculture. The research demonstrated that the applied techniques were successful tools for monitoring land-cover change in countries with limited or inexistent spatial data, where the only available information is represented in reports provided by international organizations. Results also showed that the unsupervised classification provided better land-cover change estimation and accuracy in the study area. Overall accuracies of land cover change maps using unsupervised classification algorithm were higher (74-84%) then the accuracies achieved, when the supervised classification was applied (54-68%).

**KEYWORDS:** land-cover change, classification, change vector analysis, landscape metrics.

## INTRODUCTION

The underlying driving forces behind land cover dynamics may potentially be traced to political and economic factors (Berov et al., 1998). After 1989, Bulgaria experienced major political and economic changes, moving from a socialist political system to a free-market society. This change affected the structure of all the former cooperative farms, which were transformed into thousands of new private farms, without the implementation of a system that would provide the necessary technical and economic support for a rational and appropriate use and management of the natural and human agriculture resources. Also these political and economic changes were not accompanied by the implementation of necessary instruments for monitoring of land use; as a result Bulgaria experienced a decrease

in the collection of information with respect to the use and management of major agriculture areas in the country (Berov et al., 1998).

There is an increasing need to study the effects of these socio-economic changes in the land cover in Bulgaria. However, in order to do this it is necessary the existence of reliable spatial data. Bulgaria is of one of data-poor countries with very limited spatial data sources; therefore there is a need for development of approaches that would substitute this lack of information.

The development of new models and algorithms of remote sensing science and GIS technology have made possible a more precise quantification of the spatial relationship between the two major components of the global environmental change: land cover and land use. Despite this progress remote sensing still faces serious challenges with respect to the monitoring of land cover change in countries with limited or inexistent spatial data, where the only available information are statistical reports elaborated by international organizations such as FAO. Given these limitations the question for scientists remains on how to accomplish this work and to how to support national land use management strategies in data-poor countries. In order to respond to this challenge it is necessary to develop of methodologies that integrate the existent remote sensing approaches.

The wide variety of land cover changes that occur on the landscape between certain periods of time can be monitored by different change detection methods. There is a wide variety of methods in remote sensing to analyze these changes and these methods are related to different aspects of the land cover such as land cover conversion, change in vegetation growth, change in the landscape configuration and composition, etc.

The aim of this research was to map land cover change in an area with limited ground data. In order to accomplish this, different change detection methods will be applied: Classification algorithms, Change Vector Analysis and Landscape metrics.

The specific research objectives of this study were:

To map land cover/use and estimate land cover conversion using remote sensing data and methods for the region of Plovdiv, Bulgaria, 1986-2000; To determine which classification method (supervised or unsupervised) can more accurately map the study area; To assess the relationship between land cover/use changes and the transition from planned-centralized to free-market economy in Bulgaria over the period between 1986 and 2000.

## DATA AND METHODS

### Study Area

The study area is Plovdiv County, Bulgaria (12,000 km$^2$) located in the central part of Southern Bulgaria (Figure 1) along one of the largest Bulgarian rivers ( Maritza). Elevation ranges from 15 to 625 m, the dominant slope is 15 degrees and the dominant aspect is 250 degrees. The average temperature ranges from 32°F in January to 75°F in July. The average annual precipitation is 1170 mm (Berov et al., 2003). According to the Food and Agriculture Organization (FAOSTAT) report the population growth, Plovdiv County decreased by 60% from 1970 to 2000. Plovdiv County is the second largest and second most populated county in Bulgaria. The area includes urban areas, agriculture fields, wetlands, forest and barren. The study region represents an interesting scenario of land cover change: a significant trend in urban growth and agricultural decline over the past 15 years.

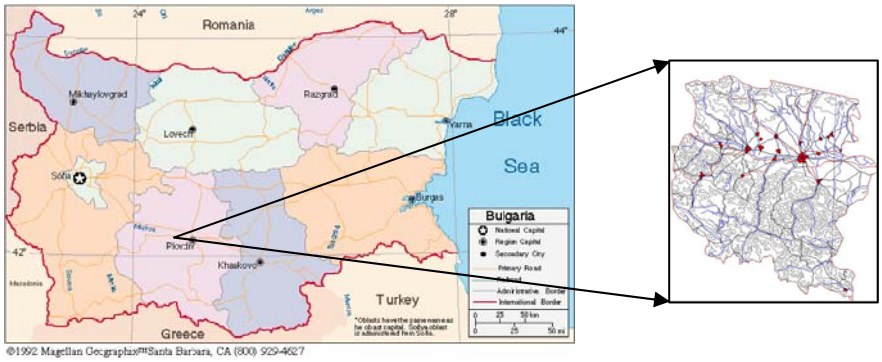



**Figure 1.** Study area of Plovdiv County, Bulgaria

# DATA

## Satellite Data

Two satellite images were acquired to map land cover changes in the Plovdiv County : Landsat 5 TM (May 22, 1986) and Landsat ETM+ 7 (June 21, 2000) (Figure 2). The spatial resolution of the satellite images was 28.5 m. Both images were registered to the UTM Zone 35 North Projection with less then 0.5 pixel root mean squared error. In order to reduce the variation in pixel digital number (DN), caused by non-surface factors as sun angle, earth-sun distance, detector calibration differences between various sensors systems, atmospheric condition and sun-target-sensor geometry (Jensen 1996), the bands from both images were radiometrically corrected using the dark object subtraction technique (Chavez, 1996). Haze was removed from each band and digital number (DN) values were transformed into reflectance values. The correction was performed according to the method designed by Markham and Barker (1985). The Solar azimuth for TM 1986 was 145.43 degree and the solar azimuth for ETM 2000 was 145.97 degree. The Solar elevation for 1986 was 48.84 degree and the solar elevation for ETM 2000 was 41.08 degree.

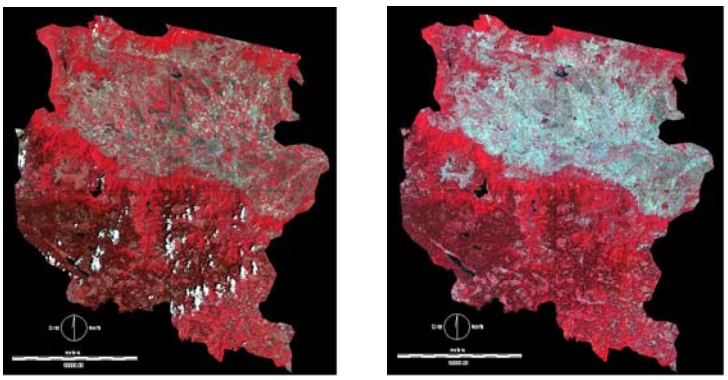


**Figure 2.** The Plovdiv County Study Area. The images are false color composites of Landsat TM 5 and Landsat ETM +7 bands 2, 3, 4 for 1986 (left) and 2000 (right), which have been topographically and radiometrically corrected.

## Ancillary Data

Slope and elevation spatial variables (Figure 3) were included with the spectral data as ancillary variables, because the results from previous studies indicated that including of these environmental variables in the classification process may help to improve the discrimination between classes and it may increase the overall accuracy of the final classified maps (Rogan et al., 2005). A 90m digital elevation model (DEM) was resampled 28.5 m and was used to produce the second environmental variable slope.

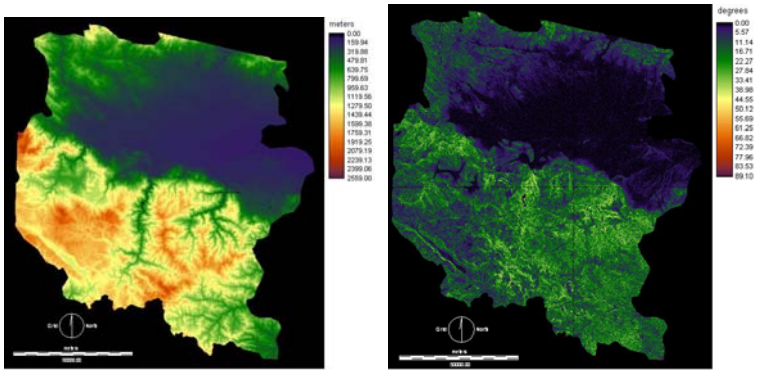



**Figure 3.** Ancillary data: Slope and elevation

# METHODOLOGY

## Unsupervised Classification ISOCLUST

An unsupervised classification was performed on the data using the ISODATA clustering algorithm. Various experiments to determine the most efficient distinction between the different land cover classes were explored using 10, 15, 20, 25 and 30 clusters. The best combination of classes was achieved deriving thirty clusters. The derived thirty classes were grouped into five desired categories: 'Agriculture', 'Barren', 'Forest', 'Water', 'Urban', using reference information from paper maps and readings and some prior knowledge of the area.

## Supervised Classification Using Neural Networks

A supervised classification was performed using cluster-sampling approach (Rogan, 2004). Training sites were derived from the satellite images using reference maps. To deliver the appropriate support size of each category the required training set for each class was determine at least ten times the number of discriminating variables (e.g., wavebands) used in the classified map (Mather 1987; Piper 1992; Peddle 1993). A backpropagation Artificial Neural Network was used to compare each pixel to the classes from the training data and to label accordingly. The following land cover categories were produced: agriculture, barren, forest, water and urban (Table 2). Slope and elevation were chosen as the only ancillary variable, because the inclusion of these variables showed a increase in the overall accuracy of the produced classification maps for 1986 and 2000: 68% and 54% respectively. The incorporation of aspect decreased the value of overall accuracy by 5%.

## Change Vector analysis (CVA)

In order to reduce redundancy in the data and highlight the vegetative qualities of the landscape, Tasseled Cap transformations (Kauth & Thomas, 1976) were performed on bands 1-5, and 7 for both satellite images. The transformation produced two new components, representing the biophysical properties of the landscape scene: brightness and greenness. Brightness represents variations in soil reflectance throughout the study area. Greenness is the contrast between the near infrared bands and the visible bands and it represents variation in vegetation cover. The inputs of brightness and greenness were used to generate images for the magnitude ands direction of variation among spectral change vectors between 1986 and 2000. These two transformed bands presented biophysically interpretable inputs for change vector analysis. The cross tabulation between these images showed the processes of cultivation, urbanization, and persistence between 1986 and 2000.

## Landscape Metrics

To quantify landscape pattern two landscape metrics were calculated: Shannon evenness (SHEI) and fragmentation index. Each of these metrics is measured by producing images for both years. Shannon evenness indicates how evenly the proportion of cover types is distributed on the landscape. Values for SHEI range between 0 and 1. Values near to 0 indicate a landscape dominated by one category, while values near to 1 indicate that the proportions of each cover type are nearly equal. The Fragmentation index indicates the breaking up of a habit or cover type into smaller, disconnected parcels.

Each metric refers to the thematic zones of the landscape for which the metric is calculated.

## Examining Land Cover Change

The TM 1986 and ETM+ 2000 images were independently classified using Neural Net Classifier and ISOCLUST classifier in five categories (Agriculture, Barren, Forest, Water and Urban). All of the final classified land cover maps were filtered using a 3x3 majority filter in order to reduce noise in the classification. CVA direction and magnitude images were created from TM 1986 and ETM+ 2000. The images representing direction change were created according following: Angles measured between 90 and 180 indicate an increase in greenness and a decrease in brightness (Lorena et al., 2002). Angles measured between 270 and 360 indicate a decrease in greenness and an increase in brightness (Lorena et al., 2002). Angles measured between 0 and 90 and 180 and 270 indicate either increases or decreases in both bands of greenness and brightness (Lorena et al., 2002). The final map was classified into three categories of 'no change', 'increased greenness and decreased brightness' and 'decreased greenness and increased brightness'. The image representing magnitude change was classified also into three categories: 'no change', 'low change magnitude', and 'high change magnitude'. These ranges were chosen,

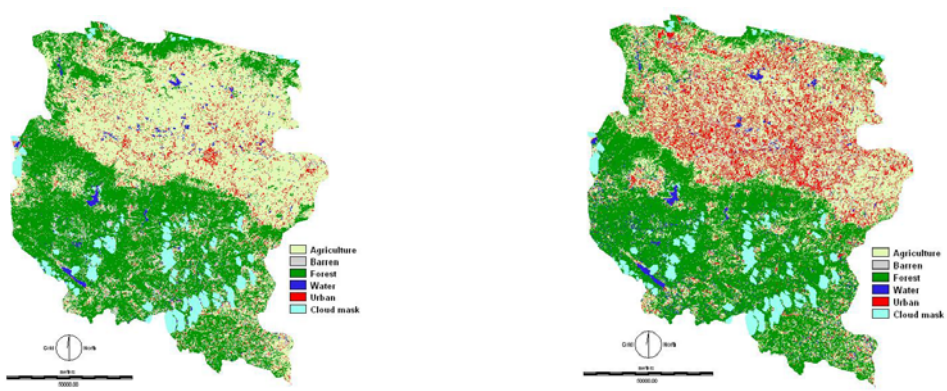
based on the following threshold values from the image histograms: high (0 to 60), low (60-167) and persistence (167-515). The change direction and magnitude values of the images were cross-tabulated and classified into three categories of 'urbanization', 'cultivation' and 'persistence'. Landscape metrics images were classified into three categories: 'increased landscape index', 'decreased landscape index' and 'no change'.

### Accuracy Assessment

Accuracy Assessment using an error matrix was assessed for the 1986 and 2000 unsupervised and supervised classification using four measures of accuracy: overall accuracy, user's accuracy, producer's accuracy and Kappa coefficient: A topographic map for the Plovdiv City area was used as ground reference information for the classification of 1986. For 2000, the classified 1996 land use map was used. A total of 30 random points for each class were taken to determine the accuracy of the classification method. Accuracy was assessed in terms of errors of omission (producer's accuracy) and commission (user's accuracy) and Kappa coefficient.

The overall map accuracy was calculated by dividing the total correct classified pixels, (major diagonal of the error matrix) by the total number of pixels in the error matrix. Overall accuracy did not take into account the proportion of agreement between datasets and it tends to overestimate classification accuracy (Congalton and Mead 1983). Producer's accuracy was calculated by dividing the total number of correct pixels in a category by total number of pixels of that category as derived from the reference data. Producer's accuracy indicates the probability of reference pixel being correctly classified and it is a measure of omission error (Jensen 1996). User's accuracy was calculated by dividing the total number of correct pixels in a category by the total number of pixels that are actually classified in that category. User's accuracy is the probability of classified pixel actually represents that category on the ground. User's accuracy is a measure of commission error (Jensen 1996). The Kappa Coefficient measures the proportional improvement of classification over purely random assignment to classes. This accuracy measure attempts to control for a chance agreement by incorporating the off-diagonal elements as a product of the row and column of the error matrix (Cohen 1960).

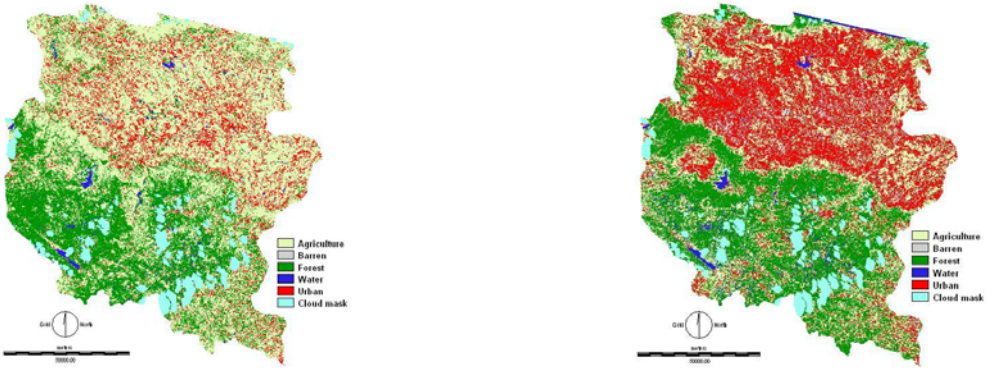
## RESULTS




**1986** **2000**

**Figure 4.** Land Cover Map 1986 and 2000 (Unsupervised Classification)

Land cover change results from the land cover unsupervised (Figure 4) classification algorithm. The land cover maps obtained from the unsupervised classification of TM 1986 and ETM+2000 respectively. The land cover conversion result show a net change in the amount of land use between 1986 and 2000, indicating that urban areas increased by 9% representing an area of 1050 $km^2$. Agriculture decreased by 3.8% or 455 $km^2$. Forest decreased by 2.6% or 317 $km^{2.}$ Barren decreased by 4.3% or 514 $km^2$ and Water increased by 1.6% or 203 $km^2$. The maps show a decrease in agriculture and forest and increase in urban from 1986 to 2000.




**1986** **2000**

**Figure 5.** Land Cover Map 1986 and 2000 (Supervised Classification).

The maps obtained from the supervised classification. Figure 5 shows the amount of change of each land category between 1986 and 2000. Urban areas are shown to increase by 19 % or 2,271 km$^{2.}$ Agriculture decreased by 25% or 2971 km$^2$. Barren increased by 3.6% or 4241 km$^2$. Forest increased with 170 km$^2$ or 1.4%. Water did not change very much; it increased with 105 km$^2$ or 1%. The map results are showing trend of high level in urbanization and high level of decreased in agriculture. According this algorithm around 1% of the agriculture areas were converted into forest areas. The main reason for this change is closely related to the process of abandonment of agriculture fields after the political and economical transition of Bulgaria to free-market economy (Hristova et al., 2004)

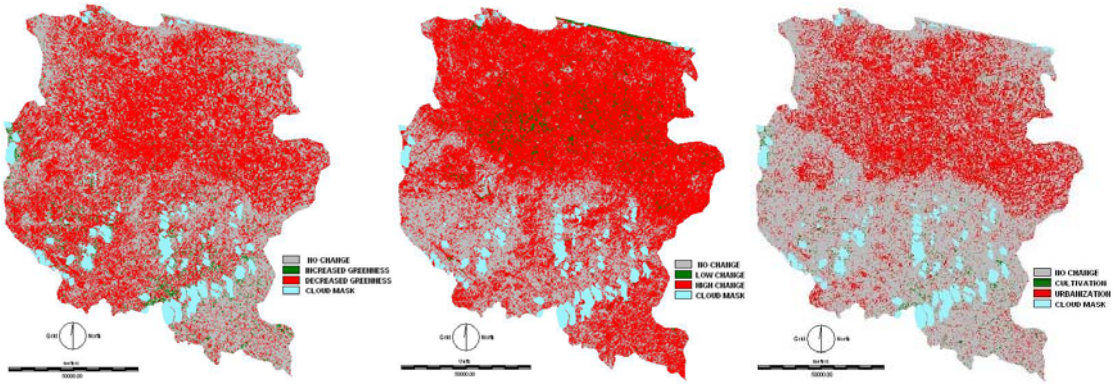
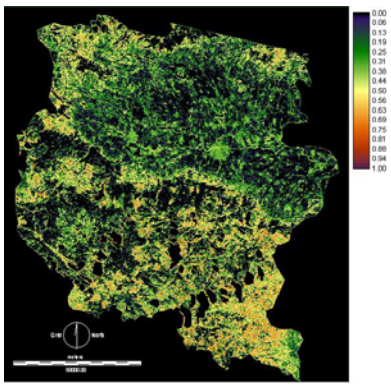



**Figure 6**. Direction of Vegetation Magnitude of Vegetation Change Classification Vegetation Change

The result of Change in Direction Image (Figure 6) shows that the areas with decreased greenness and increased brightness are areas located along the Maritza River Basin in the North Part of the study area. This change in the biophysical properties of the scene represents process of high level of urbanization from 1986 to 2000. The result of Change Magnitude Image also shows the majority of areas with high magnitude in change are clustered to the north of the study area. The crosstabulation map between change direction map and change magnitude map was classified into three categories: 'no change', 'cultivation' and 'urbanization'. A total land area of 8061 km$^2$ representing 67% of the overall land area of 11,906 km$^2$ was classified as: 'no change'. Urban areas increased by 30% or 3,637 km$^2$ while the area under cultivation increased by 1.74% or 207 km$^2$**.** Land classified as 'cultivation' contained higher levels of vegetation in 2000 than in 1986, and land designated as 'urbanization' contained lower levels of vegetation in 2000 than in 1986.



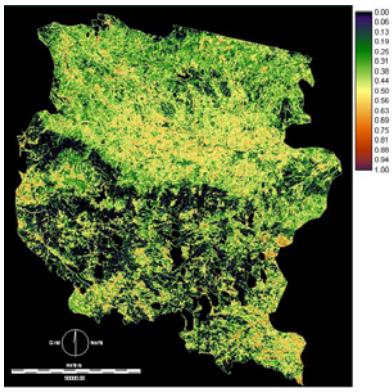
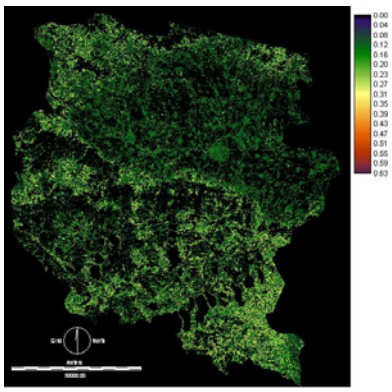


**Figure 7.** Shannon evenness image 1986 Shannon evenness image for 2000



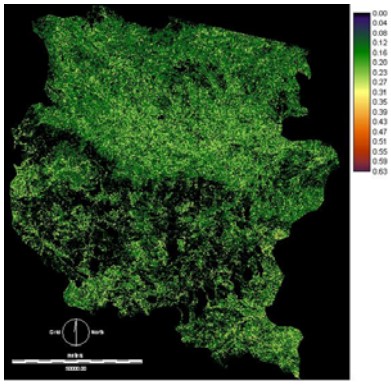


**Figure 8.** Fragmentation image for 1986 Fragmentation image for 2000

Figure 7 and 8 show the land cover change results using landscape metrics. Figure 7 shows a change in Shannon Evenness (SHEI) obtained from relative richness maps of 1986 and 2000. The range of the image values is from 0 to 1. Values close to 0 indicated that the landscape is dominated by one cover type. Values closer to 1 indicated the presence of other land cover types. The values of SHEI for 1986 are close to 0, indicating that agriculture was the dominant land cover on the landscape. Values of SHEI for 2000 are close to 1, indicating that the number or land cover types increased as result from the urbanization process.

Figure 8 shows a change in fragmentation obtained from fragmentation maps of 1986 and 2000. The values range from 0 to 1. The values close to 1, indicate that the landscape was more homogeneous, values close to 1, indicate the process of breaking land cover type into small parcels increased. The results show similar trend as SHEI. In 1986 the landscape can be characterized as more homogeneous then 2000.

## Accuracy Assessment Results

The overall accuracy for 1986 was 84% and it was with 20% higher then the accuracy performed with the supervised algorithm for 1986. According to the unsupervised classification algorithm for 1986, agriculture had the highest producer's and relatively high user's accuracy of 100% and 81%. This implies that the 100% of pixels that were correctly identified as agriculture, 81% of those pixels were actually also labeled as agriculture. The urban areas had the lowest user's accuracy of 70% and relatively high producer's accuracy of 83%. This means that 83% of pixels that were correctly identified as urban, 70% of those pixels were labeled as urban. Barren areas had the lowest producer's accuracy 67% and relatively high user's accuracy 83%. This means that 67% of the pixels belong to barren class, but 83% were labeled as barren. The Kappa Coefficient for this map was 0.8. According the accuracy assessment results using supervised classification for 1986, agriculture had the lowest producer's and

user's accuracy of 67% and 57%. This means that the 67 % of pixels that are correctly identify as agriculture, 57% of those pixels were actually also labeled as agriculture. Urban also had low producer's and user's accuracy of 67% and 59%. The Kappa Coefficient was 0.6. The accuracy assessment results from unsupervised and the supervised classification for the ETM + 2000 indicate similar results with the comparison between the two algorithms for 1986 that the producer's and user's accuracy for each class were lower using Supervised Classification Algorithm. The overall accuracy for unsupervised accuracy for 2000 was 74%, while for supervised was 54 %. According the accuracy assessment of unsupervised classification map for 2000 water had the highest user's and producer's accuracy of 90% and 77% respectively. Agriculture has the lowest producer's and user's accuracy of 60% and 67%. The result of the accuracy assessment of supervised classification algorithm for 2000 shows that urban had the highest producer's accuracy of 70% and the lowest user's accuracy of 40%. This means that the 70% of pixels that were correctly identified as urban, 40% of those pixels were actually also labeled as urban.

## DISCUSSION

As there were no other remote sensing studies of Plovdiv County to compare the results of this study to, two reference materials were used for this purpose: results from the European Land Cover Change 1990-2000 and FAOSTAT database information for Plovdiv County.

The CORINE project (Co-ordination of Information on the Environment) was implemented from the European Commission. The aim of this project was to examine land cover change information during the period 1990 to 2000 for all the European countries using 44 land cover classes. Corine Land Cover project for Bulgaria was executed with the financial support of the European Environmental Agency and the Bulgarian Ministry of Environment and Water. The methodology of this project did not include classification algorithms and the interpretation process of land cover was performed with InterChange2 software-extension of ArcView3.2.

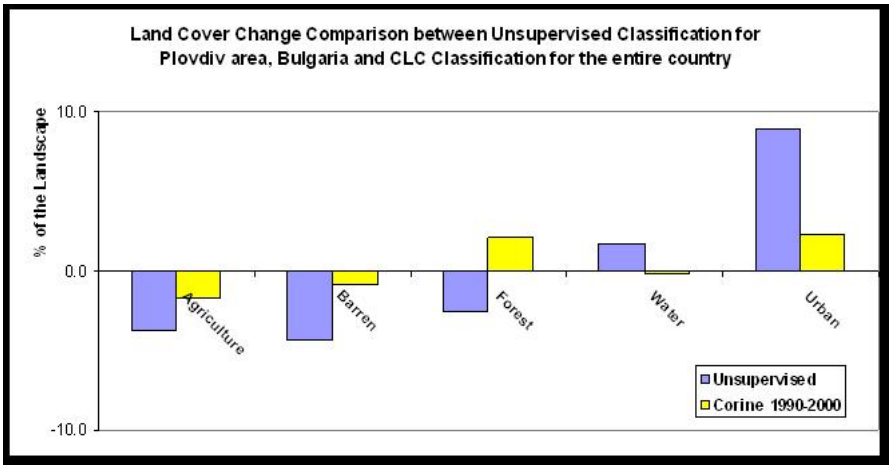



**Figure 9.** Land Cover Change Comparison between Unsupervised Classification for Plovdiv area, Bulgaria and CORINE Classification for the entire country

The comparison of the results from the CORINE classification for Bulgaria to the results from Unsupervised Classification for Plovdiv indicates a close similarity (Figure 9). Both classifications show a trend in increasing urbanization and decreasing agriculture. According to the CLC 1990-2000 project, the agriculture sector decreased in 1.7% (unsupervised classification indicated 3.6% and supervised 25.0% decrease), urban areas increased 2.3% (unsupervised classification showed 8.9% and supervised 19.1% increase). The results from unsupervised classification show a greater increase in urbanization compared to the results of urbanization changes from Corine, the visual interpretation of Corine Classificaiton does not show the high level of urbanization in Plovdiv County. The difference in the results between the two studies can be explained by two main factors: First, the CLC 1990-2000 project included the entire territory of the country, and second, the period of the analysis is four years shorter.

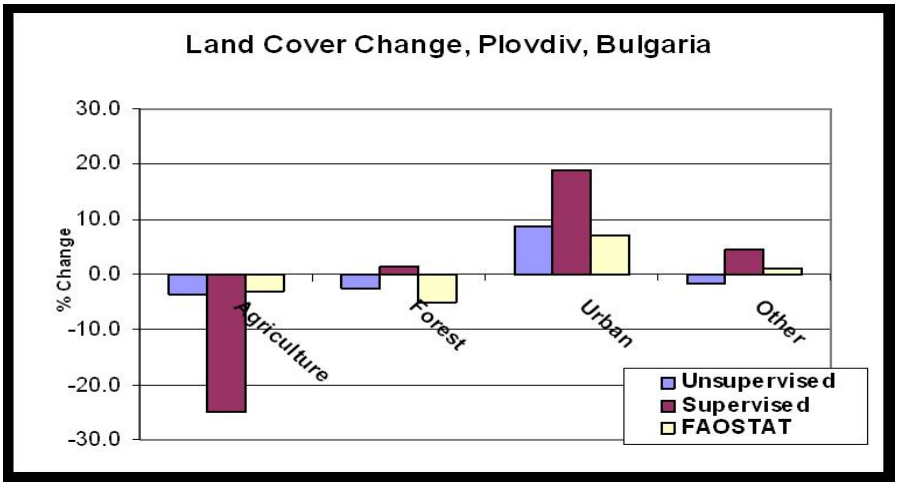



**Figure 10.** Land Cover Change Comparison between Unsupervised Classification and Supervised Classificaiton and FAOSTAT data for Plovdiv county, Bulgaria

The second reference dataset, FAOSTAT, is an online database that provides country, regional and world agricultural statistics. Statistics from FAOSTAT for Plovdiv County for the period 1986-2000 are very similar to the results from the unsupervised classification (Figure 10). FAOSTAT showed a decreased of 3.0% in agriculture, compared to unsupervised classification 3.7% and supervised classification 25% decrease. In the urban sector FAOSTAT showed an increased of 7.0% compared to unsupervised classification 8.9% and supervised classification 19.1% increase. Forest decreased 5% and unsupervised and supervised classification 2.6% and 1.4% decrease respectively.

The comparison of the accuracy analysis between unsupervised and supervised classification indicated that unsupervised classification outperformed supervised classification. The supervised method provided the lowest overall accuracy (68%, Kappa: 0.6 for 1986 and 54%, Kappa 0.43 for 2000), with higher errors in producer's and user's accuracy. The unsupervised classification increased accuracy to 84% (Kappa: 0.8) for 1986 and 74% (Kappa: 0.68) for 2000, but the producer's and user's accuracy for the land cover categories for 2000 were still low.

The quantitative results of landscape metrics and Change Vector Analysis of land use dynamics presented in this study corroborated the findings of the classification method: a high urbanization trend in the Northwest and Northeast areas of Plovdiv County in Bulgaria during the period between 1986 and 2000. The results of these analyses also provided a solid foundation for the conclusion of agriculture land lost to this process. One of the important changes detected from this study within non-forestry land use, was the increased fragmentation of agricultural areas due to urbanization and increased crop loss in the remaining lowlands. The positive changes on forest area, detected by the supervised classification provided some evidence of ecological sustainability in the region. This finding signified to some extent the success of local communities in forest conservation activities. The comparison between both change detection methods showed that Change vector analyses performed better due to it's ability to not only detect the change but also to determine the nature of the disturbance. This method can allow resource managers to observe changes over large areas and provide long-term monitoring capabilities.

The reports from FAOSTAT on Food and Agriculture Indicators for Bulgaria for the last 30 years showed a decreased of 30% in population growth and agriculture labor force. Agriculture exports decreased in 75% from 1979 to 2000. The agriculture production of wheat, milk and meat decreased in 30%. Between 1986 and 1990 agriculture was the largest source of income and employment for Plovdiv County. Given the information from FAOSTAT statistics and considering the results from this study it can be concluded that the transition from a centralized economy to free-market economy negatively affected the agriculture production of Plovdiv County from 1986 to 2000. The main driving force for this change being the economical and political changes related to the new structure of the Bulgarian society.

Other possible driving forces of land cover changes in Plovdiv, Bulgaria between 1986 and 2000 could be the population change. Comparative assessments of population and land use suggest that population growth is negatively correlated with the expansion of agricultural land, and positively correlated with urban growth and land intensification.

Bulgaria's cities experienced rapid growth after 1944. In 1946 only Sofia and Plovdiv had populations numbering over 100,000, by 1990 there were ten cities having populations exceeding 250,000. In 1990 nearly one-third of Bulgaria's population lived in the ten largest cities; two-thirds of the population was urban. Although the urban birth rate declined after the mid-1970s, large-scale migration from rural areas to cities continued through 1990. At the same time, migration from cities to rural areas increased in more than double from the 1960s to the 1980s, mainly because more mechanical and service jobs became available in agriculture during that period. In cities such as Sofia and Plovdiv, where industrialization started earlier, the population stabilized and the repercussions of rapid population growth slowed down in the 1980s. The population of the average Bulgarian city grew by three to four times between 1950 and 1990. The rapidity of this growth caused some negative trends: the cities often lacked the resources to meet the needs of their growing populations, in particular, housing and social services could not grow fast enough. The cities' great need for social resources in turn diverted resources from smaller, more scattered population centers. The overall rural to urban migration pattern caused shortages of agricultural labor, especially in the villages surrounding large cities. The government discouraged new industries from locating in outlying areas because of the lack of workers.

## CONCLUSION

This research project investigated land cover changes in Plovdiv County, Bulgaria from 1986 to 2000. The results from the applied change detection techniques indicate that there is a significant increase in urban areas and decrease in agriculture. An unsupervised classification algorithm was the most suitable approach to detect changes over large areas and to provide long-term capabilities for monitoring land cover change in data-poor regions. The similarity of results from this research and the official statistics from FAOSTAT proved that remote sensing methods provides reliable and cost effective information for land use mangers and planners. This study demonstrates that remote sensing offers great analytical tools to relate socio-economic and political changes in the society to land cover change. Both classification methods showed agreement with respect to identifying the areas of change, the change vector analysis and landscape metrics also proved this finding. The difference in the two classification methods lay in the estimated quantification of the land cover conversion. Supervised classification appeared to over-classify the pixels from the images due to a large variety of reflectance (especially urban areas).

From a visual examination of the map of land change from the CORINE study it appears that their methodology misclassified the areas where land change occurred and it under-represented the magnitude of the changes.

From these results it can be suggested that change detection methods applied in this study should be adopted for the land cover change analysis of large areas without reliable spatial data.

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