Landsat 8 vs. Landsat 5: A comparison based on urban and peri-urban land cover mapping

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Keywords: Landsat 8, SVM, GEOBIA, Peri-urban, Classification

Abstract

An image dataset from the Landsat OLI spaceborne sensor is compared with the Landsat TM in order to evaluate the excellence of the new imagery in urban landcover classification. Widely known pixel-based and object-based image analysis methods have been implemented in this work like Maximum Likelihood, Support Vector Machine, k-Nearest Neighbor, Feature Analyst and Sub-pixel. Classification results from Landsat OLI provide more accurate results comparing to the Landsat TM. Object-based classifications produced a more uniform result, but suffer from the absorption of small rare classes into large homogenous areas, as a consequence of the segmentation, merging and the spatial parameters in the spatial resolution (30m) of Landsat images. Based exclusively on the overall accuracy reports, the SVM pixel-based classification from Landsat 8 proved to be the most accurate for the purpose of mapping urban land cover, using medium spatial resolution imagery.

Introduction

Thematic mapping is a prerequisite for several environmental and socioeconomic applications (Blaschke, 2010) and it is typically based on remotely sensed data and image classification (Chrysoulakis et al., 2010). One of the main issues when generating Land Cover (LC) maps from digital images is the confusion of spectral responses from different features. The accuracy of the classified map depends on the spatial and spectral resolution, the seasonal variability in vegetation cover types and soil moisture conditions. Landsat series of satellites are the most common Earth Observation (EO) data sources for LC mapping, even for urban, peri-urban and rural areas. Landsat Thematic Mapper (TM) started providing multispectral observations in 1984. In 2004, NASA sponsored the creation of the Global Orthorectified Landsat Dataset (Tucker et al., 2004). Recently, with the launch of the Landsat 8, carrying the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), a new orthorectified dataset (LIT) became available (Roy et al., 2014). Landsat OLI, TIRS and TM imagery, having a nominal spatial resolution of 30m are considered as low resolution (LR) (Strahler et al., 1986). Nevertheless, it can be used for mapping urban and peri-urban areas, especially in areas with moderate population density and complex landscape. On the contrary, high resolution (HR) imagery provided by sensors such as Worldview-2, is normally used in urban LC mapping. However, such datasets are costly and their analysis needs much more computing resources than the respective Landsat ones. The above LR and HR cases will be bridged by the expected Copernicus Sentinel-2, with a spatial resolution of 10 meters in visible and near infrared bands and a revisit time of 5 days (Drusch et al., 2012). Sentinel-2 is therefore expected to be used complementary with Landsat 8 for urban areas mapping and monitoring. Urban and peri-urban LC classification with the use of LR imagery is challenging due to the spectral mixing of different surface elements and the landscape complexity. Conventional pixel-based classifiers, such as Maximum Likelihood (MLC) (Jensen, 2000), cannot effectively handle the mixed-pixel problem in complex urban/peri-urban areas. Alternative approaches, such as the Support Vector Machine (SVM) (Foody and Mathur, 2004) and Geographic Object-Based Image Analysis (GEOBIA) (Blaschke, 2010) provide better results although they do not address the mixed-pixel problem.

Huang et al. (2002) compared classification products from four different classification algorithms implemented on Landsat TM data and found that SVM outperformed the rest three approaches. Similar results were provided by Duro et al. (2012), who examined the performance of three classification algorithms SPOT-5 high resolution geometrical (HRG). They found that in the...
pixel-based classification results, even if the overall accuracy between the above three approaches (Decision Tree-DT, Random Forest-RF and SVM) was not statistical significant, the SVM classification achieved better discrimination between riparian vegetation and grasslands and thus obtained less speckles in such areas. Robertson and King (2011) analyzed Landsat TM images from different periods and found that the accuracies for the object-based classifications were lower than the respective accuracies of pixel-based methods. This could be related to the segmentation process and the scale factor that is selected for the segmentation. Duro et al. (2012) provide similar results, using SPOT imagery, while Gong et al. (2013) create a global landcover dataset from Landsat TM and ETM+ by applying SVM. Classification maps can be acceptable depending on the purpose of the classification product (input for hydrological or fire propagation models, cartography purposes, etc.). The objective of this work is to compare the performance of Landsat 8 OLI against Landsat TM for urban and peri-urban LC mapping, using common training and validation data.

Classification algorithms

To assess the differences of OLI and TM for LC mapping, the performances of the following image classification methods were compared:

- Pixel based MLC and SVM.
- ENVI Feature Extraction with SVM & k-NN and Feature Analyst (FA).
- Sub-pixel Linear Spectral Mixture Analysis (LSMA).

MLC and SVM have been extensively discussed in previous studies and thus we will not discuss them (Lu and Weng, 2007).

Concerning Object-based Machine Learning methods, the FA and ENVI Feature Extraction were used in this study. FA is an adaptive-learning software from Overwatch TEXTRON Systems (Optiz and Blundell, 2008). Deductive learning algorithms and techniques are used to model visual object-recognition processes. Mixed approaches of Artificial Neural Networks (ANN), Decision Trees (DT), Bayesian learning and k-Nearest Neighbor approaches are combined to achieve high precision in image classification. Spectral and spatial information from the imagery are combined to classify individual pixels, based on target and background signatures. Predefined search kernels, based upon the concept of "foveal" vision, which focus on the central and edged areas of a moving window, are used. Minimum object sizes are utilized to account for the spatial context in the classification procedure.

ENVI Feature Extraction is a module for extracting information from HR panchromatic or multispectral imagery, based on spatial, spectral and texture characteristics (Höfling and Neubert, 2008). Its workflow includes segmentation with scale level and merge settings; square kernel sizing; examples selection and attribute assignment (spectral, texture and spatial which are combined to classify the pixels) and algorithm selection. K-Nearest Neighbor (k-NN) with variable neighbors (1, 2, n) (Collins et al., 2004); and Support Vector Machines (SVM) with 4 kernel types (Radial, Linear, Polynomial and Sigmoid) (Lu and Weng, 2007) have been used. Recent studies (Tsotzos and Argialas, 2008) have proven that SVMs have excellent results compared to the classic MLCA comparison of recently developed algorithms for a complex landscape could provide better insights on the performance of the selected classification algorithms.

Spectral Unmixing methods, deal with the mixed pixel problem. The radiance measured by the sensor is assumed to be a combination of the radiances of the underlying end-members (Keshava, 2003). The result of LSMA is a set of abundance images depicting the fractional cover of each end-member in each pixel. Because of its effectiveness in handling the spectral mixture problem, LSMA has been widely used in many fields, such as mapping of land-cover types (Lu et al., 2003). In urban studies, LSMA has been proved useful for estimating impervious surface and vegetation abundance and thus improving the urban classification (Lu and Weng, 2004; Mitakka et al., 2012). Due to the complexity of the urban surface, in many cases, assigning one end-member for each class in the classification scheme is not enough. In these cases the Multiple Endmember Spectral Mixture Analysis (MESMA), a method that combines more than one end-members for each class, is employed (Powell et al., 2007). The aforementioned methods are part of commercial software and thus accessible to use and replicate depending on the availability of ground truth data. Application of those methods to Landsat 8 data may address a wide range of classification approaches in complex urban and peri-urban landscapes and they have the potential to provide valuable information for improving the LC mapping accuracy.

Study area and datasets

The study area covers the catchment of Rafina Municipality (Fig. 1), an area of 123 km², located in Attika, Greece. It is a recently developed area, close to the “Eleftherios Venizelos” International Airport of Athens and to the Attiki Odos highway (A6 highway). This highway connects the study area with the city of Athens, favoring urban sprawl (Chrysoulakis et al., 2013). It should be however noted that, given the present economic status of Greece the urbanization rate in the study area has been decreased after 2010. The study area consists of urban settlements, cultivated areas, low vegetated slopes, isolated pine forest areas and a stream network, which host riparian vegetation.

Two Landsat images were used in this study: Landsat TM (May 1, 2010); and Landsat 8 OLI (April 30, 2013). Both Landsat images were terrain corrected by USGS (USGS, 2013). All bands of images have been used (USGS, 2014). A HR orthophotomap produced by aerial images at 0.5 m spatial resolution, acquired in summer 2010 was made available by the Mapping and Cadastral Organization Greece (MOOG, www.okef.gr). This image was used as an ancillary dataset for the definition of the classification training areas, as well as for the accuracy assessment.

Methodology

Classification scheme

Knowledge of the study area and visual inspection of the available images assisted in developing the classification scheme. False color composites, RGB: 4-3-2 for TM and RGB: 5-4-3 for OLI clearly depicted the forest vegetation in dark red, the water associated vegetation in bright red and the urban surface materials in light bluish tones, while it was difficult to distinguish dry cultivated areas and low vegetation. The latter one was possible using the true color combination RGB: 3-2-1 for TM and RGB: 4-3-2 for OLI. Urban surface materials were split into two categories (a) bright impervious surfaces, which included the bright reflectance from buildings; and (b) dark impervious surfaces which include roads, sidewalks, driveways, parking lots and industrial areas (Table 1). An important step for the development of the classification scheme and the selection of the training sites is the separability between spectral signatures of the different elements. For this purpose, the Transformed Divergence (TD) metric was used to evaluate the class separability.

For the sub-pixel classification, the proposed scheme was modified to match the requirements of MESMA. In this study, a
simplified approach of MESMA was applied to ensure capturing the end-member variability, without surcharging computation cost. End-members representative for each of the classes of the above scheme were defined plus end-members for a “soil” class. An end-member library was thus constructed, including spectra corresponding to each class of the scheme, following a hierarchical approach (Herold and Roberts, 2010). Spectra were collected from the images by visual interpretation, ensuring the purity of the pixels, using the Pixel Purity Index and auxiliary information from the available HR imagery. A set of 61 spectra were included in the library assigned to the vegetation class, 58 to the impervious class and 43 to the soils class. For all samples of the constructed library, MESMA was applied using a set of possible combinations to ensure capturing the variation arising from more than one vegetation, impervious, or soil types.

### Table 1

<table>
<thead>
<tr>
<th>No.</th>
<th>Abbreviation</th>
<th>Class name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BI</td>
<td>Bright impervious</td>
</tr>
<tr>
<td>2</td>
<td>DI</td>
<td>Dark impervious</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>Forest – dark green vegetation</td>
</tr>
<tr>
<td>4</td>
<td>R</td>
<td>Riparian – bright green vegetation</td>
</tr>
<tr>
<td>5</td>
<td>LVMI</td>
<td>Low vegetation with bushes the minor</td>
</tr>
<tr>
<td>6</td>
<td>LVMA</td>
<td>Low vegetation with bushes the major</td>
</tr>
<tr>
<td>7</td>
<td>RC</td>
<td>Row crops</td>
</tr>
<tr>
<td>8</td>
<td>RT</td>
<td>Roof tops from clay</td>
</tr>
</tbody>
</table>

### Accuracy assessment

To assess the accuracy of the classification, ground truth data were collected. The identified validation sites are individual pixels, having the pixel size of Landsat (30 m × 30 m). These sites represent locations of known LC classes. A two-stage approach for the collection of ground truth data was adopted in this study. In the first stage, fieldwork was conducted in May 2013, at locations where the LC type was not possible to be defined from the available HR images. A mixture of orchards and tree vegetation among some abandoned cultivation land seemed that existed in some of these areas and field observations were necessary to clarify this situation. A GPS and a compact digital camera with a built-in GPS were used to collect the ground truth data at several locations. In a second stage, the above-mentioned HR orthophotomap, along with recent HR imagery available from Google Earth, were used. Using the collected observations described above, two independent datasets were created: (1) the training samples used in LC classification, and (2) the validation samples. In total, 130 ground truth samples were collected by both field work and HR image interpretation. To assess the LSMA accuracy, more detail within the classes was necessary. Cells of 30 m × 30 m, at the locations of ground truthing, were used. For each cell, the surface cover types were digitized from the available HR orthophotomaps (Fig. 2). LSMA classifications results were then linked to these cells and statistics were computed on the differences between the actual and the extracted fractional covers.
The comparison of the different classification results in LC mapping was based on their accuracy assessment results. An error matrix was created for each resulting thematic map and the metrics of overall accuracy (OA), producer’s accuracy (PA) and user’s accuracy (UA) were calculated. From the 130 randomly distributed validation points in the study area, the minimum representation threshold for each LC class was set to 10 points. Only the classification algorithms which resulted in over 80% OA were compared in this study. For the highest accurate results, change detection test has been applied to investigate the differences among the results and what extend have impact in the spatial extend of the landcover. The accuracy assessment of the sub-pixel classification had to be performed differently. The reference dataset was digitized for the same sample of 130 points as described above. The percentage of each component estimated from the HR orthophotomaps (reference fraction) was compared to the corresponding fraction in the resulted fractional image (modeled fraction). The correlation between reference and modeled fractions were reported in terms of slope, intercept, and correlation coefficient, where, in an ideal case, the slope of the relationship would equal one, the intercept zero, and the correlation coefficient ($R^2$) would approach one. Two additional error metrics were used to evaluate the accuracy of the fraction estimations, mean absolute error (MAE) and bias.

Gray level co-occurrence matrix

Gray level co-occurrence matrix analysis (GLCM, Gadkari, 2004) has been applied in the NIR band, as this is the most altered band in terms of range (0.76–0.90 in TM vs. 0.85–0.88 in OLI). For selected landcover types, we calculate the mean values of four features named (1) Homogeneity (HOM), (2) Contrast (CON), (3) Entropy (ENT) and (4) Angular Second Moment (ASM) (Table 7). HOM and ASM are measures of homogeneity for the image. CON is a measure of the contrast or the amount of local variations present in an image (Haralick et al., 1973). ENT measures the disorder or complexity of an image. The ENT is large when the image is not texturally uniform and many GLCM elements have very small values. Complex textures tend to have high entropy. HOM and ASM decrease with increasing image quality while CON and ENT increase with increasing image quality (Gadkari, 2004).

Results and discussion

Pixel-based classification results

The main elements of the anthropogenic environment detected in the study area are compact urban areas; small settlements; isolated building infrastructures; and the main road network in the central and southwest area. The main elements of the natural environment are; forest islets; an extended area of mixed cultivations to the south; low vegetated areas in the north; and an extended network of streams with riparian vegetation. The per-pixel classification maps from Landsat TM and OLI images are shown in Figs. 3 and 4. All maps share the same legend (Fig. 3). A closer visual inspection of the classification maps, reveals their main difference, which is the overestimation of the bright impervious areas by Landsat TM and the more accurate estimation of the same element by Landsat OLI. Same issues are observed for the riparian vegetation, in the transitional zones between the stream and the vegetated areas.

The results of the pixel-based classification accuracy are shown in Table 2. The landcover maps meet the 80% limit for classification results acceptance. However, even if the statistics indicate high accuracy, a close inspection on the classified images point out several misclassification cases. In the case of Landsat TM, for both MLC and SVM, bright impervious areas in the urban environment were confused with the RT class, transition zones between vegetations classes were confused with R and in some areas cultivations were classified as R. Furthermore, some bare areas uphill were classified as RT, due to the spectral similarities. RC appear sparsely uphill;
this may happen due to the similar spectral characteristics of abandoned fields and areas with LVMI. On the other hand for Landsat 8, in both MLC and SVM results, BI and transition zones between natural vegetation classes have better accuracy, as shown in Fig. 4. Finally, in both images, natural impervious areas (bare rock) were classified as BI (man-made) due to their spectral similarity.

Table 2
Accuracy statistics for the pixel-based classification algorithms.

<table>
<thead>
<tr>
<th></th>
<th>TM</th>
<th>OLI</th>
<th></th>
<th>MLC</th>
<th>SVM</th>
<th>MLC</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>OA (%)</td>
<td>83.85</td>
<td>84.62</td>
<td>86.15</td>
<td>89.23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA (%)</td>
<td>85.63</td>
<td>87.25</td>
<td>89.63</td>
<td>91.63</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UA (%)</td>
<td>82.75</td>
<td>83.63</td>
<td>74.00</td>
<td>87.75</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Although all classification results of pixel-based analysis achieved an overall accuracy over 80%, the SVM classification of OLI data obtained the highest OA. As shown in Fig. 6, the classification of BI, DI, F, R and RT were particularly successful, while few RC were confused with the two low vegetation classes. The same is observed within some RC areas, since fields with low vegetation share similar spectral characteristics. The low vegetation categories have confusion between themselves and the row crops but still OLI results have higher accuracy from TM. These differences were also analyzed by applying change detection techniques in the highest accuracy results among the pixel based classifiers. In the urban environment (BI, DI, RT) in OLI, the 14% of the area is classified as urban while in TM 15.6%. In the natural environment, riparian vegetation in OLI cover the 18% of the area while in TM 15%. The other vegetation classes have better representation in OLI (52.2% vs. 48% in TM). Cultivations have lower cover in OLI (17%) comparing to TM (20%). Derived results thus agree on the high capacity of SVM to classify accurately mixed landscapes such the urban–peri-urban environment (Huang et al., 2002; Duro et al., 2012) using Landsat data.
Object-based classification results

ENVI Feature extraction with two object-based algorithms was used for both TM and OLI. These are the K-Nearest Neighbor (k-NN) with variable neighbors and the SVM with the 3 kernel types. FA method was also employed with five different training scenarios, as shown in Table 3. Training scenario is the combination of the selected image bands used in the analysis, the kernel window shape, and the learning algorithm.

Classification maps resulted from ENVI Feature Extraction suffer from the absorption of small classes by more homogenous areas, as well as by an irregular pattern. This is a result of the incapability of the kernel window to provide more degrees of freedom in the construction and the shape of the window. Aftereffect several noticeable errors that can be observed in the thematic maps are shown in Figs. 5 and 6 (results with the lower and higher OA are presented).

Classification maps for TM and OLI derived from the FA approaches were more concrete and visually acceptable (Fig. 7). FA allows the user to select one pixel as the size of the window and in the case of Landsat imageries is very useful. The errors in the classification of the pixel for the predefined classes were less, compared to the previous results. Landsat TM imagery classification was prone to the overestimation of some classes, while Landsat OLI results were more accurate and tend to have a proper classification. Riparian vegetation is a major part of the study area and the transition zones between it and the dry, shrubby vegetated areas cannot be easily separated. Furthermore, isolated build areas within the cultivated land, or elsewhere in the natural environment cannot be easily separated, when object-based techniques are employed. Although, the advanced radiometric characteristics of the Landsat OLI have more accurately separate the above mentioned elements. In Fig. 9, the classification results obtained the higher overall accuracy, for both TM and OLI, are presented.

Having a close inspection at the results of Landsat TM, only the SVM2 classification obtained an overall accuracy of 80.8%. The classifications provided accuracies lower than 80% and are therefore rejected. On the other hand, by employing the FA approach for different input scenarios, the overall classification accuracy, was
greater than 80% (Table 5). Among them, the highest overall accuracy was achieved by the third scenario (AFE3) (Fig. 7). For Landsat OLI, most of the employed object-based classification methods met the accuracy standard set in this study (Table 4). Furthermore, all the FA implementation scenarios for OLI resulted in overall accuracies greater than 80% (Table 5). The first scenario (AFE1) obtained the highest overall accuracy (86.92%) (Fig. 7). Comparing the performance of the two Landsat images on the different object-oriented approaches, the object-based machine learning LC maps from Landsat OLI were more spatially homogenous than the respective maps provided by the feature extraction as well as from Landsat TM.

**Sub-pixel classification results**

Sub-pixel classification results are presented in the form of fraction images, depicting the abundance of each cover type in the pixel. The fraction images for the three land surface types derived by LMSA are shown in Fig. 8, for both TM and OLI.

The color scale intensity represents the abundance of each surface component in each pixel. Areas that appear red in the fraction images represent higher abundances, while blue areas indicate lower abundances. A closer inspection at the fraction images reveals the same pattern observed in the pixel-based and object-based derived results. Built-up areas, road network and the new airport are included in the impervious fraction image. Surfaces covered with rocks are also included in the impervious fraction image, as expected. Vegetated areas like the cultivation plains, the riparian areas and the forests are well represented in the vegetation fraction image. Areas with non-photosynthetic vegetation, as well as open fields are represented in the soil fraction image as well. The slope, intercept, R-squared error, MAE and bias for all fraction images for both TM and OLI scenes are presented in Table 5. Fig. 9 shows the scatterplots of the reference vs. the estimated fraction values for the vegetation, impervious and soil fraction images for Landsat TM and OLI.

Both the estimated accuracy measures (Table 6) and the scatterplots indicate overestimation of the vegetation fraction by LSMA and underestimation of the soil fraction. The reason for this behavior is the vegetation phenology in combination with the collection of end-members. End-members were collected from the image as pure spectra representing each cover type. However, in the study area and particularly at the acquisition season of both images (spring), it is challenging to have pure bare soil pixels. Although an attempt was made to avoid this effect, some end-members representing the soil component contain mixture of low vegetation, which explains the LSMA diverge for soil and vegetation fraction images. In addition, the data used for validation have been assembled using VHR imagery acquired during the summer period, which introduces further uncertainty to vegetation phenology due to the season change. A better agreement between the abundance estimations and the validation data is observed in the case of the impervious surface cover, with a slight underestimation for both TM and OLI, as observed in Fig. 9(a) and (d) and the respective values in Table 6. Both TM and OLI, shown in Fig. 7(a) and (d), adequately captured the impervious surface cover, revealing the same pattern. The visual interpretation of derived fraction images and the estimated accuracy measures lean in favor of OLI comparing to the TM.

### Discussion

The medium spatial resolution of both TM and OLI resulted in an interclass spectral variation, while the limited number of spectral bands resulted in an increased spectral mixing. Starting from the classification results for Landsat TM, poor classification performance was observed for some classes and confusion for others. For example, low vegetation with bushes, in some cases was classified as riparian or row crops. Likewise, some row crops, mainly vineyards, were classified as riparian vegetation. In addition, natural impervious areas were classified as man-made impervious areas by the pixel-based algorithms. Forest areas,
man-made bright impervious areas, clay roof tops, man-made dark impervious areas and low vegetation with bushes (minor) were the classes that obtained higher classification accuracy. Riparian vegetation was sometimes classified as forest, or as low vegetation with bushes (major), whereas row crop areas were mixed with low vegetation and forests. The latter is explained due to the phenology of some cultivation types like the orchards and the vineyards, but also due to the increased moisture that these cultivations preserve in comparison to the rest vegetation types (Xie et al., 2008). For both images, the results of GEOBIA classification and object-based feature extraction with the k-NN provided the poorest performance, while SVM slightly exceeded the standard of this study (80%). This happened due to the limitation on the control of the kernel shape and the number of pixels that were used for its implementation, which omitted isolated pixels with different spectral characteristics from their surroundings. Finally, by using Landsat OLI, the FA approach provided the most accurate results, in terms of spatial shape and classes contingency, independently on the input classification scenario settings.

For the same classes and using the same training and validation data, OLI obtained better accuracies in both pixel-based and object-based classifications. Some confusion among classes existed also in OLI results, but not as much as in the case of TM, while the separation of vegetation types and impervious areas (manmade vs. natural) was performed with higher accuracy. For both sensors, the class with the lowest user’s accuracy was the LVMA, reflecting its high interclass spectral variability. An interesting point is that the highest OA (89.2%) for OLI was observed for the pixel-based SVM, followed by the machine learning object-based (FA) with the OA of 86.92%. The narrower NIR band and the higher signal to noise ratio of OLI contribute to these results. To evaluate this hypothesis, a classification has been applied in both TM and OLI using the same bands by using the algorithm with the highest accuracy (pixel based SVM). The results show that even if the OA drop in both cases (6% in OLI and 8% in TM), OLI presents better accuracy (7% better than TM).

Four texture features in five selected areas have been calculated for both images (mean values) (Table 7). All results show that OLI has better image quality as all values of HOM and ASM are lower than those of TM and all values of CON and ENT are higher than these of TM. These textural information shows that the NIR band of OLI has much finer texture with more information as a consequence of the narrowing of this band to avoid the effect of the water vapor absorption (0.825 μm).

Pixel-based classification of medium resolution images, such as the Landsat TM and OLI, preserves the spectral information derived from the isolated pixels and classify them appropriately in the class that spectrally belongs to (Lu and Weng, 2007; Robertson and King, 2011). Object based classification methods on the other hand, operate on blocks of pixels and assign isolated pixels according to the block of the surrounding majority (Blaschke, 2010). In this work, the area under study consists of several isolated elements, pixels corresponding to isolated buildings, cultivations, urban green areas, etc. By using object-based algorithms, these areas cannot be preserved in the LC map because of the lower limit of the employed kernel window. Alternatively, FA uses a more flexible kernel window in its input representation, enabling the use of a greater number of kernel shapes, with no lower pixel limit in the respective kernel windows. Manhattan input representation pattern is suggested in extracting information of extended LC features such as the vegetation, wetlands and impervious surfaces (VLS, 2007). The selection of different seasonal images can help achieving better separation among some LC types like row crops and low vegetation. In this study, both TM and OLI images were acquired at the same period of the year, when low vegetation and some row crops are often confused with riparian vegetation. During this

Table 6
Accuracy measures for TM and OLI images for the different end-members assumed in LSMA method.

<table>
<thead>
<tr>
<th>Impervious</th>
<th>Vegetation</th>
<th>Soil</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TM</strong></td>
<td><strong>OLI</strong></td>
<td><strong>TM</strong></td>
</tr>
<tr>
<td>Slope</td>
<td>0.7500</td>
<td>0.7400</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0999</td>
<td>0.0310</td>
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<tr>
<td>R-squared</td>
<td>0.6931</td>
<td>0.8124</td>
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<tr>
<td>MAE</td>
<td>0.1282</td>
<td>0.1071</td>
</tr>
<tr>
<td>Bias</td>
<td>0.0178</td>
<td>-0.0533</td>
</tr>
</tbody>
</table>
Fig. 8. LSMA maps from Landsat LT5 TM (a)–(c) and LT8 OLI (d)–(f).
period, the above vegetation types appeared phenologically similar, therefore they could not be separated effectively. It has to be noted here that the scope of the work is not to monitor the landcover changes in the area. A solution to this is the use of multiseasonal images (Lunetta and Barlogh, 1999). The selection and use of multiseasonal images is a rather easy task nowadays, having access to the free Landsat imagery, as well as to other free datasets in different scales and to the forthcoming Sentinel 2 data. In addition, the classification approach should be selected by applying different criteria related to the use of the resulted maps.

**Conclusions**

In this study, a set of different classification methods were applied to Landsat TM and OLI data in order to assess and compare their performance in classifying peri-urban areas. In highly fragmented landscapes, like the peri-urban area of Athens, by analyzing medium resolution imagery such as provided by Landsat TM and OLI, using advanced methods like the SVM, it is possible to result in highly accurate classification maps. SVM can maintain the spatial characteristics of such landscapes, like the fragmentation and the isolation of elements in the space and is the most appropriate algorithm in our study, the landcover analysis of an urban environment. LC maps were produced using different classification methods. Results indicated that for this type of satellite imagery, SVM pixel-based classification method keep the fragmented elements of the landscape and provide a more accurate classification product. Between Landsat TM and OLI, the latter produce more accurate LC maps. On the other hand, analyzing medium resolution images using GEOBIA approaches, generally results in LC maps with homogeneous shapes, which in the case of fragmented areas leads to lower classification accuracies, due to the integration of spatially limited elements into the neighbor classes. This phenomenon is intensified by some limitations of the algorithms used in the GEOBIA classification procedures. It is finally concluded that, if highly fragmented landscapes are studied using Landsat, the performance of the object-based feature extraction algorithms is poorer than the performance of the respective object-based machine learning approaches. The major difference between the above two main categories, apart from the specific algorithms per se, is the ability to control the shape and the size of the kernel window in machine learning approaches.

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**Table 7**

GLCM data for Landsat OLI and TM.

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>HOM 13LT8</th>
<th>HOM 13LT5</th>
<th>CON 14LT8</th>
<th>CON 14LT5</th>
<th>ENT 15LT8</th>
<th>ENT 15LT5</th>
<th>ASM 16LT8</th>
<th>ASM 16LT5</th>
</tr>
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<tbody>
<tr>
<td>Cultivations</td>
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**Fig. 9**. Scatterplots of the reference vs. the estimated fraction values for the impervious (a–d), vegetation (b–e) and soil (c–f) fraction images for TM and OLI.
References


