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

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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 (30 m) 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 (L1T) became available (Roy et al., 2014). Landsat OLI, TIRS and TM imagery, having a nominal spatial resolution of 30 m 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

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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 (Opitz 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 (Hölbling 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 (Tzotzos 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; Mitraka 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 km^2, located in Attika, Greece. It is a recently developed area, close to the "*Eleftherios Venizelo*" 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 (MCOG, www.okxe.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