OBJECT-BASED CLASSIFICATION OF LAND COVER TYPES USING LIDAR AND SATELLITE IMAGES

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ABSTRACT: The purpose of this research is to conduct a land cover mapping using optical, microwave, and LiDAR images. The study area is situated near the town of Thetford in the Breckland district of Norfolk, England. The site has such land cover classes as forest, cropland, barren land, residential buildings, water, and it covers 900ha. To extract the land cover class information, an object-based classification technique is applied and a rule-base to separate the mixed classes is developed. Before applying the rule, a multi-resolution segmentation is used to obtain all possible image objects to be considered for further analysis. The rule-base uses a hierarchy of rules describing different conditions under which the actual classification has to be performed. The final result indicates an overall accuracy of 96.57% for the object-based classification. Overall, the research indicates that the object-based method that uses a thoroughly defined segmentation and a well-constructed rule-base can significantly improve the classification of land cover objects, and the output may be effectively used for a spatial decision-making.

1. INTRODUCTION

Traditionally, satellite RS data sets with different spectral, spatial and temporal properties have been efficiently used for a land cover mapping at a large spatial extent. However, because of the recent rapid urbanization process and related urban studies, the demand on land cover maps at a better resolution has been raised with evidence by numerous biophysical and socio-economic studies, specifically in city areas (Yan et al. 2015). Now very high resolution optical images are being widely applied for urban area mapping, nonetheless, with the emergence of new spatial technologies, LiDAR data is increasingly used for different urban applications. As LIDAR is accurate and quick to survey, the urban planners can easily know where things are and what are the changes happened. Although most research studies mainly focus on the analysis of geometric components of three dimensional LiDAR data point clouds, there has been an increasing interest in investigating the intensity data, integrate it with other multispectral images and use the integrated datasets for land cover classification (Yan et al. 2015, Weinmann et al. 2017).

Over the past few years, object-based classifications have been increasingly used for different mapping applications. These methods have been developed in order to improve the traditional pixel-based classification techniques. Unlike the pixel-based classifications that are based on the information of each pixel in the data, the object-based classifications are based on the information from a set of similar pixels called image objects. The image objects are groups of pixels that are similar to one another based on the spectral properties, size, shape, and texture, as well as context from a neighborhood surrounding the pixels. The object-based method uses a segmentation process and iterative learning algorithm to achieve a semi-automatic classification procedure that demonstrates more accurate results than traditional pixel-based methods (Grenzdörffer, 2005; Hay and Castilla, 2006, Liu and Xia, 2010, Weih and Riggan, 2012).

The aim of this study is to classify landcover types and produce a reliable map of the Thetford area, England using optical Sentinel-2A, microwave Sentinel-1 images and LiDAR data. To extract the land cover class information, an object-based classification technique based on a multi-resolution segmentation and constructed rule-base have been applied.

2. TEST AREA & DATA SOURCES

In this research, the Thetford forest area, situated near the town Thetford in the Breckland district of Norfolk, England, has been selected. Figure 1 shows location of the study area. Thetford Forest is the largest lowland pine forest in Britain and is located in a region straddling the north of Suffolk and the south of Norfolk in England. (Skipper & Williamson, 1997). It was created after the First World War to provide a strategic reserve of timber, since the country had lost so many oaks and other slow-growing trees as a consequence of the war's demands. By the end of the First World War the economic position of the large landed estates in England were bleak and particularly acute in areas of poor soil like Breckland. Farms were left untenanted and land became derelict. At that time, the Forestry Commission had been established. In 1922, the first purchases of land were made over 80% of the lands (Skipper and Williamson, 1997).

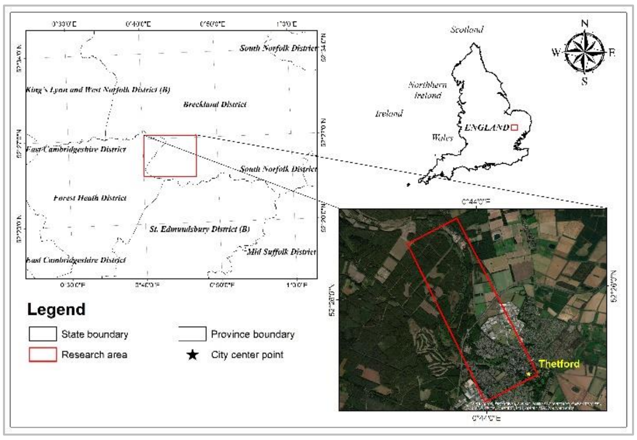

Figure 1. Location map of the test site.

The satellite data used in the current study consisted of a Sentinel-2A optical and Sentinel-1 radar images acquired in July 2021 as well as airborne LiDAR image with 1m spatial resolution recorded in 2016. Figure 2 shows remotely sensed images of the research site. The area of interest is extended from the west to the east about 1.8km and from the north to the south about 5km.

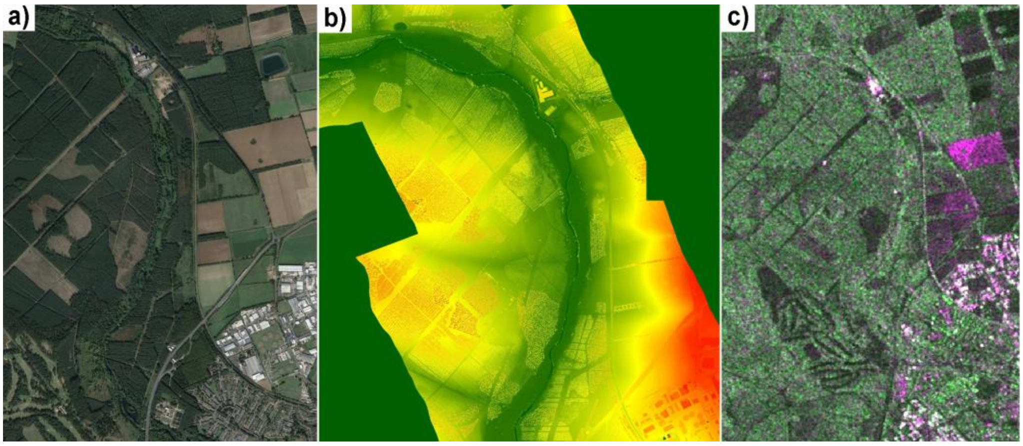

Figure 2. The study area: a) Sentinel 2A image; b) LIDAR image; c) Sentinel 1 image.

3. RESEARCH METHODOLOGY

For the classification of the satellite images and Lidar data, an object-oriented approach as implemented in eCognition developer 9, has been used. For the analysis, two processing steps can be distinguished. The first step is the segmentation of the data into homogenous segments, followed by the assignment of these segments to discrete classes. These steps can also be used alternately, i.e. the classification results of one processing step can be input for a subsequent segmentation. In the following sections, image segmentation and classification will be examined followed by the integration of ancillary data.

Given the limitations inherent in optical RS imagery and the difficulties posed by unique urban environments, LiDAR has been valued for providing important complementary types of information, such as elevation data and structural features, that have the potential to improve tree species classification accuracy (Hollaus et al. 2009). In order to carry out image processing analysis, the optical and radar images were thoroughly analyzed in terms of brightness and geometric distortion. The images were of a good quality, therefore, it was not necessary to apply any radiometric corrections.

Image segmentation

In this processing step, we need to identify homogenous image segments. Depending on the data and goal of the analysis, different degrees of homogeneity can be desirable. Segmentation is controlled by parameters: scale, color and shape, selected by the user (Baatz and Schäpe, 2000). Scale controls the maximum allowed heterogeneity per segment. Leaving all other parameters constant, a larger scale will result in larger segments. The parameters color and shape sum to one and determine how much color and shape information is used for the segmentation process. The shape parameter is further divided into compactness and smoothness. A high value for compactness leads to smaller and very compact segments, more suitable for manmade objects, while a high value for smoothness leads to segments optimized to have smooth borders, more suitable for natural objects.

Different data sets such as laser and satellite images can be segmented simultaneously and their influence on the segmentation process can be adjusted by weights. Nevertheless, a stepwise approach was chosen here due to very different information content as well as different scaling of the data, allowing more control over the segmentation process. An initial segmentation was carried out on the basis of the satellite images as their information content is larger than of the laser image. Discrimination of different land cover types, especially of vegetation and built-up areas can be done very easily using this data. A second segmentation was performed one level below the initial segmentation and here only the laser information was used. This allows a separation of both built-up areas and vegetation on the basis of height, improving both the identification of roads as well as that of shrubs and grassland. In a third segmentation level between levels 1 and 2, segmentation was performed, based only on absolute height differences, at the same time staying within the boundaries defined by the original segmentation of the satellite image.

Image classification

For each segment, identified in the previous processing steps, a large number of features are available for the classification. In order to combine the relevant information and establish the necessary classification rules, a class hierarchy has been set up. At this stage, five land cover classes were identified. In addition, a class for unclassified segments was introduced. Nine types of features were used for the classification: mean, ratio, standard deviation, brightness, normalized difference water index (NDWI), soil adjusted vegetation index (SAVI), green leaf algorithm (GLA), foliage cover index (FCI), and normalized difference vegetation index (NDVI). Mean refers to the mean value of all pixels present in a segment, e.g. mean nDSM is the mean height of all pixels within a segment. The ratio refers to the mean spectral values of one band divided by the sum of all spectral values, e.g. ratio blue is the ration of the Sentinel blue band with the sum of all other Sentinel bands. Brightness is the mean of all spectral bands and the NDVI is an index calculated from the red the near-infrared bands, giving an indication as to the vegetation intensity (Lillesand and Kiefer, 1994), NDWI is an index calculated from the green, near-infrared bands, SAVI is an index Calculated red the near-infrared bands, GLA is an index calculated red, green, and blue bands, FCI is an index increased GLA index (Table 2).

Each class was described by one or more of these features. Thresholds for each feature are given in the form of fuzzy functions. Classification is performed in a hierarchical manner, examining each segment whether its membership is high enough for classification or not. If it is so, then the segment is assigned to the appropriate class, all remaining segments are examined for the next class until all segments are classified. Table 1 shows an overview of the features used for each class. A combination of spectral as well as height information was used to successfully determine different classes.

Table 1. The used indices and related equations.

Indices	Formula
NDVI (Normalized differance Vegetation Index)	(NIR - Red) / (NIR + Red)
SAVI (Soil Adjusted Vegetation Index)	(1+L) (NIR−Red) / (NIR+Red+L)
GLA (Green Leaf Algorithm)	(2 * Green - Red - Blue) / (2 * Green + Red + Blue)
FCI (Foliage cover index)	F = 2.57*GLA+1.94
NDWI (Normalized Difference Water index)	(Green - NIR)/(Green + NIR)

4. RESULTS AND DISCUSSION

In the object-based method, after an image is segmented into appropriate image objects, the image is classified by assigning each object to a class, based on features and criteria set by the user. To obtain useful information, the segmentation process splits an image into unclassified *'object primitives'* that form the basis for the image objects. Segmentation and the resulting characteristics of object primitives and eventual image objects are based on shape, size, color, and pixel topology controlled through parameters set by the user. The values of the parameters define how much influence spectral and spatial characteristics of the image layers will have in defining the shape and size of the image objects. The user modifies the settings depending on the objective of the study, as well as the image quality, available bands and image resolution. As a general rule, reliable image objects should be as large as possible, but small enough to show details of interest (Gronemeyer. 2012).

In the current study, the object-based classification of landcover types consists of three processes, namely, segmentation, rule-based classification and accuracy assessment. A general diagram of the constructed object-based classification is shown in Figure 3.

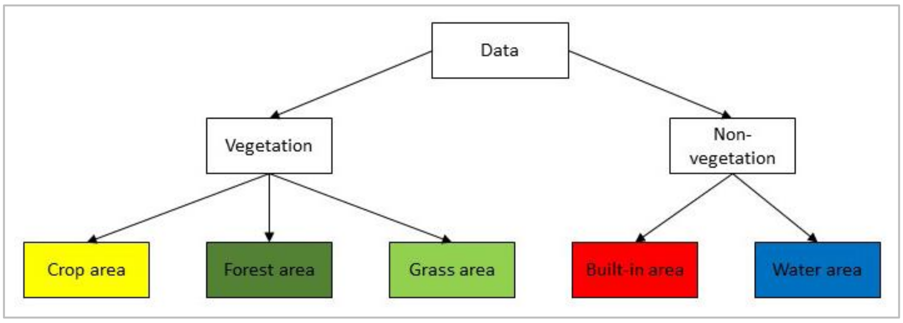

Figure 3. A general diagram of the constructed object-based classification method.

Before the classification can be performed the data must be segmented. The initial segmentation was carried out using only the Sentinel 2 image (scale: 10, color/shape: 0.1, smoothness/ compactness 0.5). The result is the separation of spectrally distinct land cover types. Before the next segmentation, the first layer must be deleted. Below the remaining layer, a new segmentation is performed only on the basis of nDSM data (scale: 3, color: 1). Here, no shape information is used for the segmentation. The borders of the segments derived in the segmentation of the satellite image limit how much a segment may grow. From this follows that spectrally similar image objects can be separated on the basis of height (e.g. roof), but spectrally different objects not combined based on height (e.g. tree next to a house).). The final segmentation level is created between level one and two, only based on nDSM data and using a spectral difference value of 1, again within the boundaries defined by the segmentation of the satellite image (Figure 4).

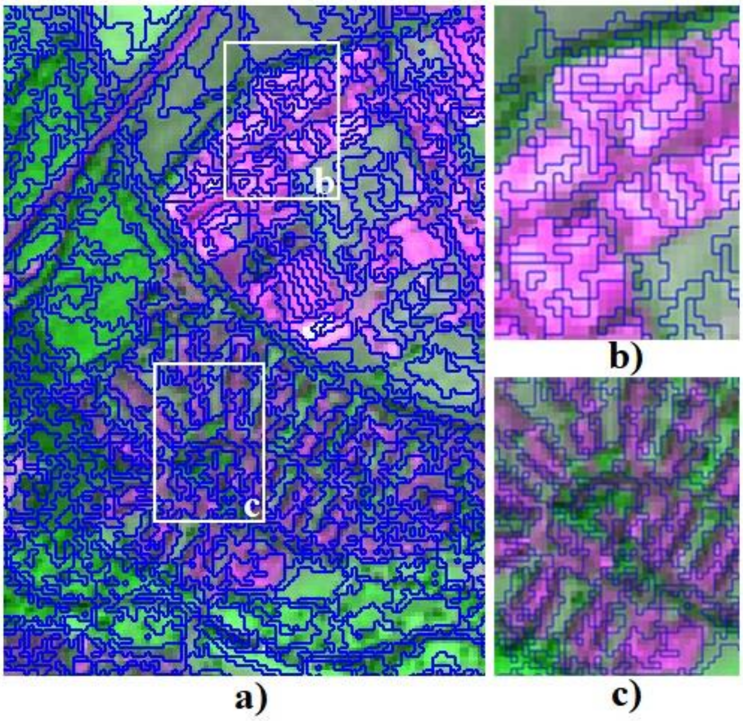

Figure 4. Final multiresolution segmentation.

The segmentation parameters to be selected by the user are interrelated to each other. It is impossible to directly find a set of proper segmentation parameters at one time. Users have to repeatedly select a set of segmentation parameters and test them through a trial-and-error process, until a reasonable segmentation result is achieved or the user does not want to continue the trial and error anymore (Zhang et al. 2010). Classification is performed on the final segmentation level using the features defined in Table 2.

Table 2. Features used for classification.

Class	**Features used**
Vegetation	NDVI Brightness SAVI
Forest	FCI GLA
Crop	Mean nDSM SD
Not vegetation	Not Vegetation
Build	SAVI NDVI Ratio Blue SD
Water	NDWI Mean nDSM SD

nDSM: normalized digital surface model
NDWI: normalized difference water index
NDVI: normalized difference vegetation index
SAVI: soil adjusted vegetation index
FCI: foliage cover index
GLA: green leaf algorithm
SD: standard deviation.

The result of the segmentation (Figure 5) is basically a product of two separate segmentation procedures, where the first limited the extent to how far a segment may grow in the later segmentation. This assumes that basic land cover types can be separated successfully in the first segmentation stage and only need refining, based on the Lidar data within each land cover type. An example is sealed areas, which in most cases can be separated very well from non-sealed areas. Differentiation of different types of sealing is much more difficult. and often impossible using only optical data. Here, Lidar gives us the opportunity to identify land cover types such as forests and building with a high degree of accuracy.

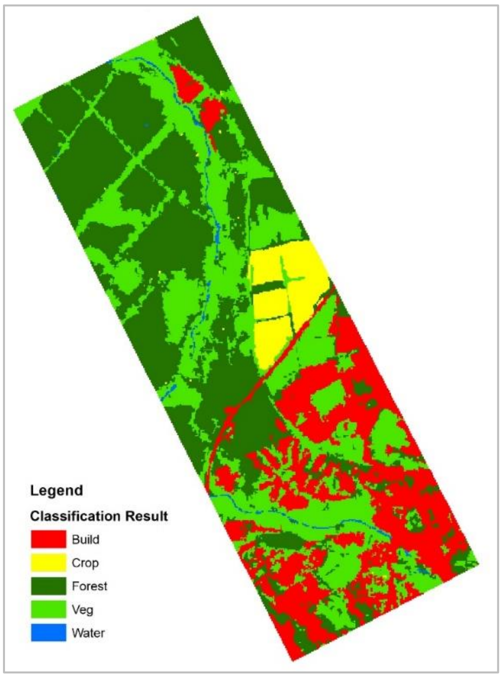

Figure 5. Final result of the object-based classification.

Generally, accuracy assessment is required for evaluating the quality of the performed classification results or for identifying a suitable classification method by comparing different classification outputs in a selected study area (Moran, 2010). An error matrix is a most frequently used approach in accuracy assessment method from which other important accuracy assessment elements, such as overall classification accuracy, producer's accuracy, user's accuracy, and Kappa coefficient can be derived (Wulder et al. 2006; Foody 2009; Li et al. 2011). In the current study, overall classification accuracy has been performed, and the final result indicated an overall accuracy of 96.57% for the object-based classification.

5. CONCLUSIONS

The aim of the research was to produce a reliable land cover map using optical and radar satellite images along with Lidar data. As a test site, the Thetford forest area, situated near the town Thetford in the Breckland district of Norfolk, England, was selected. For the extraction of the land cover class information, the object-based classification technique was applied. To derive the thematic information, initially, to the selected RS images multi-resolution segmentation was applied. Then, the obtained image objects were classified into different land cover classes using the developed rule-base. The rule-base contained a hierarchy of rules, describing different conditions under which the actual classification should to be accomplished. The final result indicated an overall accuracy of 96.57% for the object-based classification.

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