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Using mixed objects in the training of object-based image classifications

Hugo Costa *, Giles M. Foody, Doreen S. Boyd

School of Geography, University of Nottingham, Nottingham NG7 2RD, UK

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ABSTRACT

Image classification for thematic mapping is a very common application in remote sensing, which is sometimes realized through object-based image analysis. In these analyses, it is common for some of the objects to be mixed in their class composition and thus violate the commonly made assumption of object purity that is implicit in a conventional object-based image analysis. Mixed objects can be a problem throughout a classification analysis, but are particularly challenging in the training stage as they can result in degraded training statistics and act to reduce mapping accuracy. In this paper the potential of using mixed objects in training object-based image classifications is evaluated. Remotely sensed data were submitted to a series of segmentation analyses from which a range of under- to over-segmented outputs were intentionally produced. Training objects were then selected from the segmentation outputs, resulting in training data sets that varied in terms of size (i.e. number of objects) and proportion of mixed objects. These training data sets were then used with an artificial neural network and a generalized linear model, which can accommodate objects of mixed composition, to produce a series of land cover maps. The use of training statistics estimated based on both pure and mixed objects often increased classification accuracy by around 25% when compared with accuracies obtained from the use of only pure objects in training. So rather than the mixed objects being a problem, they can be an asset in classification and facilitate land cover mapping from remote sensing. It is, therefore, desirable to recognize the nature of the objects and possibly accommodate mixed objects directly in training. The results obtained here may also have implications for the common practice of seeking an optimal segmentation output, and also act to challenge the widespread view that object-based classification is superior to pixel-based classification.

1. Introduction

Information on the Earth's surface such as land cover and related environmental processes is of great importance for a plethora of applications, for example for decision-making on issues related to agriculture and food security (Fritz et al., 2013; Gardi et al., 2015), monitoring the distribution of species (Martin et al., 2013; Tuanmu and Jetz, 2014), and modelling of the Earth's climate (Luyssaert et al., 2014; Mahmood et al., 2014). For this reason, thematic mapping through a classification analysis is a very common application of remote sensing. Over the years substantial progress has been made in remote sensing-based mapping, and today there are many ways through which a classification analysis can be conducted (Lu and Weng, 2007; Momeni et al., 2016).

A key decision needed during a classification analysis is on which basic spatial unit to use. Considerable use of the pixel, the basic spatial unit of a digital image, and per-pixel based classification has been common for decades. However, grouping spatially connected pixels into objects by means of an image segmentation analysis, and using the object as the basic spatial unit has become very popular in recent years (Blaschke et al., 2014). The objects obtained from an image segmentation analysis may, in principle, form a more suitable spatial unit than the pixel for land cover mapping as they should relate to natural spatial units (e.g. fields) unlike pixels which are artificial units defined more by the sensing system than the properties of the ground. The use of objects comprising multiple pixels can also aid the calculation of potentially useful discriminatory variables such as descriptors of image texture (Laliberte and Rango, 2009).

There are, however, fundamental issues and assumptions of classification that often appear to be ignored or incompletely addressed in object-based image analyses. For example, it is common for the objects produced from the segmentation analysis to be routinely and unquestioningly used as if pure in the classification (e.g. Goodin et al., 2015; Shimabukuro et al., 2015; Uddin et al., 2015). However, this is often not the case, mainly for two reasons. First, remotely sensed data inevitably comprise a proportion of mixed pixels whatever the spatial resolution used (Addink et al., 2012; Cracknell, 1998; Fisher, 1997), which cannot be accommodated by traditional image segmentation. For example, Wu (2009) found that 40–50% of the pixels of an urban area represented in multispectral IKONOS data (4 m resolution) were mixed. Second, image segmentation often produces mixed objects as a result of under-segmentation error. This type of error corresponds to

* Corresponding author.
E-mail address: hugoagcosta@gmail.com (H. Costa).

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situations such as the failure of the image segmentation analysis to define a border splitting two land cover classes, thereby generating a single object containing more than one class (Clinton et al., 2010).

Failure to satisfy the assumptions of classification can greatly degrade the quality of the land cover map produced ultimately. In particular, the specific case of under-segmentation error (Gao et al., 2011; Hirata and Takahashi, 2011; Wang et al., 2004) is a problem throughout the classification process as mixed objects can degrade class training statistics, they cannot be appropriately allocated to a single class, and any such allocation must to some extent be erroneous (Heumann, 2011). Action is therefore needed to address the impact of these mixed units. That said, deviation from the assumptions of classification can, however, sometimes be made in each of the main stages of a classification analysis (e.g. Foody, 1999a). Specifically, impure units can be accounted for in training (Eastman and Laney, 2002; Foody, 1997; Hansen, 2012; Zhang and Foody, 2001), class allocation (Dronova et al., 2011; Foody, 1996; Wang, 1990), and testing a classification (Binaghi et al., 1999; Foody, 1995; Stehman et al., 2007). For example, van de Vlag and Stein (2007) generated objects based on remotely sensed data, classified them using fuzzy decision trees, and produced fuzzy error matrices in accuracy assessment. However, little research has been undertaken on the use of mixed units in training object-based image classifications.

Typically, the objects used in training are assumed to be pure (i.e. contain a single class), but a range of options are available if mixed objects are encountered. For example, the analyst could seek to simply ignore the problem, act to exclude the mixed cases, or adopt procedures that can accommodate the mixed nature of the units (Foody, 1999a, 1997). In object-based classification, the presence of mixed objects in training is sometimes addressed beforehand by deliberately favouring over-segmentation, that is, producing numerous small objects at the segmentation stage (Boyden et al., 2013; Cánovas-García and Alonso-Sarría, 2015; Dronova et al., 2012; Van Coillie et al., 2008). However, this approach may be sub-optimal (Dorren, 2003; Gao et al., 2011; Hirata and Takahashi, 2011; Kim et al., 2009; Mishra and Crews, 2014) and is unlikely to remove all impure objects (Zhou et al., 2009; Zhou and Troy, 2008). Another solution sometimes adopted is the exclusion of mixed objects from the production of training statistics (Cai and Liu, 2013; Dean and Smith, 2003; Dronova et al., 2011; Güttler et al., 2016). In this way, the mixed units, which do not satisfy key assumptions of the analysis, are excluded so that the analysis can proceed with suitable data. Excluding mixed objects has, however, the consequence that the size of the training data sets will be reduced, and this could limit the quality of the resulting training statistics. This issue is particularly relevant in object-based classifications as the pool of potential training units is typically relatively small at the outset (Ma et al., 2015). Excluding mixed objects from the pool of selectable objects can exacerbate the challenge of finding a sufficient number of training objects (Mui et al., 2015; Wang et al., 2004).

Another issue to take into account while excluding mixed objects is the criteria according to which an object should be considered as mixed. It is unclear whether an object containing a very small fraction of pixels corresponding to a minority class should be excluded from training because there is the chance of those minority pixels having a negligible impact on the training statistics produced. For example, Cai and Liu (2013) excluded from training all objects whose dominant class occupied <90% of the objects' area. The effect of issues such as threshold selection have not been investigated in detail (Li et al., 2016) and is most likely to be dependent on several factors, such as the remotely sensed data used and the land cover classes mixed (Dronova et al., 2011).

The assumptions of a classification also impact on the way training data sets should be used. For example, the training stage of a supervised classification should be designed in relation to the chosen classifier as different algorithms use the data differently. Specifically, with a standard statistical classifier, such as the maximum likelihood classification, it is important that each class is described appropriately which often requires a relatively large and representative training sample (Ediriwickrema and Khorram, 1997; Hagner and Reese, 2007; Paola and Schowengerdt, 1995; Richards and Kingsbury, 2014) while the use of a small sample of deliberately selected extreme and atypical samples may be more suited to non-parametric classifiers, such as a multilayer perceptron neural network, support vector machine, and classification tree (Foody, 1999b; Foody and Mathur, 2006; Hansen, 2012; Pal and Foody, 2012). Critically, the nature of the data used in training a classification should be acknowledged and addressed.

In this paper it is argued that it is not necessary, or even desirable, to exclude mixed objects from training an object-based image classification. In particular, it is possible to turn the apparent problem of mixed units into an asset, as with mixed pixels in per-pixel classification (Foody, 1997), recognizing that each individual mixed unit can be a source of training data on more than one class, and that mixed units can be used in training. Here, the potential of using mixed objects in training an object-based image classification is evaluated. A series of image segmentation analyses were undertaken from which training objects were selected, resulting in training data sets that varied in terms of size and proportion of mixed objects. The mixed objects generated at the segmentation stage and encountered at the training stage are included in the set of objects used to estimate training statistics, and the classification outputs produced by two classifiers are evaluated in relation to a conventional analysis using only pure objects. Thus, the work sets out to test the hypothesis that mixed objects may be used in the training of object-based image classifications to increase the accuracy with which land cover may be mapped from remotely sensed data.

2. Materials and methods

2.1. Study area and data sets

The analyses focused on a test site of approximately 45,000 ha in northern Portugal (Fig. 1). The area corresponds to the downstream part of river Lima where the city of Viana do Castelo is settled. A diverse range of land cover types are present in the study area, and five land cover classes were defined: Artificial surfaces, Agricultural areas, Forest and semi-natural areas, Open spaces with little or no vegetation, and Wetlands and water bodies.

A Portuguese map, "Carta de Ocupação do Solo" of 2007 (COS2007), was used as reference data set (Fig. 2a) in training and testing the object-based classifications. This map was produced by the Portuguese mapping agency (Directorate-General for Territorial Development) through visual interpretation of aerial imagery and use of auxiliary data such as field work and the national forest inventory. Land cover is represented according to a nomenclature similar to that used in this study in the third of a total of five hierarchical thematic levels used to map land cover with a minimum mapping unit of 1 ha (Caetano et al., 2010). As a guide to the thematic accuracy of the map, the overall accuracy is 96.82 ± 1.01% at the 95% confidence level for the thematic detail used in this article, 5 classes, and the producer's accuracy for each of the

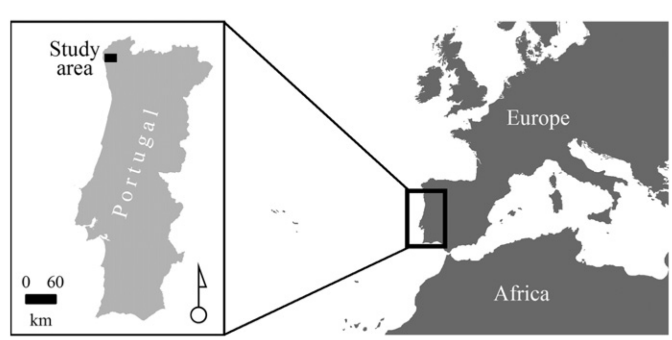

Fig. 1. Location of the study area.