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Training set size, scale, and features in Geographic Object-Based Image Analysis of very high resolution unmanned aerial vehicle imagery

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ABSTRACT

Unmanned Aerial Vehicle (UAV) has been used increasingly for natural resource applications in recent years due to their greater availability and the miniaturization of sensors. In addition, Geographic Object-Based Image Analysis (GEOBIA) has received more attention as a novel paradigm for remote sensing earth observation data. However, GEOBIA generates some new problems compared with pixel-based methods. In this study, we developed a strategy for the semi-automatic optimization of object-based classification, which involves an area-based accuracy assessment that analyzes the relationship between scale and the training set size. We found that the Overall Accuracy (OA) increased as the training set ratio (proportion of the segmented objects used for training) increased when the Segmentation Scale Parameter (SSP) was fixed. The OA increased more slowly as the training set ratio became larger and a similar rule was obtained according to the pixel-based image analysis. The OA decreased as the SSP increased when the training set ratio was fixed. Consequently, the SSP should not be too large during classification using a small training set ratio. By contrast, a large training set ratio is required if classification is performed using a high SSP. In addition, we suggest that the optimal SSP for each class has a high positive correlation with the mean area obtained by manual interpretation, which can be summarized by a linear correlation equation. We expect that these results will be applicable to UAV imagery classification to determine the optimal SSP for each class.

1. Introduction

Geographic Object-Based Image Analysis (GEOBIA) is a systematic framework for geographic object identification, which combines pixels with the same semantic information into an object, thereby generating an integrated geographic object, before recognizing the geographic object using GIS spatial analysis or a mature classification algorithm, i.e., Neural Networks (NN), Maximum Likelihood (ML), Support Vector Machines (SVM), and Random Forests (RF). GEOBIA is also a new and evolving paradigm, which was designed specifically for high resolution remote sensing image data, in contrast to the pixel-based approach (Benz et al., 2004; Liu et al., 2006; Blaschke, 2010; Myint et al., 2011; Addink et al., 2012; Blaschke et al., 2014). Indeed, GEOBIA has become a popular alternative for land cover and land use classification (Radoux and Bogaert, 2014). Since the first international GEOBIA conference in Calgary, Canada, the unique advantages of GEOBIA have attracted the attention of scholars throughout the global field of remote sensing (Hay and Castilla, 2008; Powers et al., 2012; Arvor et al., 2013; Costa et al., 2014; Blaschke et al., 2014). GEOBIA has many advantages as a new paradigm in the diverse fields of remote sensing because it is readily combined with GIS to provide a complete vector map of land use types, which can be used directly for GIS analysis (Arvor et al., 2013). However, the pixels that belong to the same object cannot be combined into one complete object accurately due to the uncertainty of segmentation, which is a process used to partition a complex image scene into non-overlapping homogeneous regions (Witharana and Civco, 2014). This is because over-segmentation and under-segmentation

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always occur due to inappropriate segmentation parameters, especially the Segmentation Scale Parameter (SSP) (Kim et al., 2011; Zhang et al., 2013). Thus, many problems are caused by segmentation, most of which are also known to affect pixel-based image analysis. These problems include the strategies used for sample selection, feature selection, accuracy assessment, and change detection, as follows. (1) Which of the classes should we label for over- or under-segmentation during sampling? (2) What are the best features for classification and what is the most appropriate feature selection method (e.g., spectral, textural, geometrical, or semantic features). (3) In GEOBIA, the planar vector layer leads to many objects being generated by segmentation; thus, should we consider these objects as single points to evaluate the accuracy, or return to evaluation at the pixel level by stacking the classified layer and reference layer? In other words, is the point-based accuracy evaluation method or the area-based method more suitable, and how does the segmentation scale affect them?

In terms of the scale problem, multiresolution segmentation (MRS) has proved to be one of the most successful image segmentation algorithms in the GEOBIA framework (Witharana and Civco, 2014). This algorithm is relatively complex and user-dependent, where the scale, shape, and compactness are the main parameters manipulated by users to control the algorithm (Witharana and Civco, 2014). The scale parameter is considered to be one of the most important variables because it controls the relative size of the image objects, which has a direct impact on the subsequent classification steps (Kim et al., 2011; Myint et al., 2011; Hussain et al., 2013; Drăguţ et al., 2014). Blaschke et al. (2014) also note that semantically significant regions are found at different scales, which makes it important to adjust the scale parameter during segmentation to obtain optimal results. However, many of the specific applications used for identification rely on trial and error to determine the optimal scale parameter based on the experience of the operators (Laliberte and Rango, 2009; Stefanski et al., 2013; Ma et al., 2014; Witharana and Civco, 2014). Clearly, this approach is not desirable because it is user-dependent (Johnson and Xie, 2011). Thus, many methods have been proposed for determining the scale parameter (Drăguţ et al., 2010, 2014; Johnson and Xie, 2011). However, most of these proposed methods are based on specific imagery and none considers the actual cover characteristics when determining the optimal SSP. To implement a multiscale hierarchical classification method, we usually need to set different segmentation scale parameters from top to bottom, thereby ensuring the extraction of objects with different sizes (Kim et al., 2011; Duro et al., 2012). This means that the optimal segmentation scale is different for various ground objects (e.g., cropland, buildings, water bodies, and woodland). Therefore, we tried to consider the actual size of the ground objects to determine their optimal SSP in the present study. We also aimed to elucidate the specific relationship between the optimal SSP and the characteristics of actual objects.

Multiscale GEOBIA can generate dozens and sometimes hundreds of variables for classifying imagery (Duro et al., 2012). In particular, for UAV VHR imagery, the number of features in each object can exceed 200 at each scale with eCognition software, which increases at finer scales due to the soaring number of segmented objects. Analyzing these features can be more computationally intensive than the analysis of photos obtained from piloted aircraft or satellites (Laliberte and Rango, 2009). The high number of features also complicates the construction of a classifier and it leads to the curse of dimensionality or Hughes phenomenon (Pal and Foody, 2010). Therefore, feature selection is an important step when improving the accuracy and efficiency of classification. Two goals of feature selection are obtaining a more thorough understanding of the underlying processes that influence the data and identifying discriminative and useful features for classification and prediction (Guyon and Elisseeff, 2003). Feature analysis based on pixels is performed more frequently compared with GEOBIA (Novack et al., 2011). Several feature reduction techniques are also used frequently in remote sensing, including InfoGain (Novack et al., 2011), Relief-F (Novack et al., 2011), RF algorithms (Pal and Foody, 2010), Correlation-based Feature Selection (CFS) (Hall et al., 2009), and principal components analysis (Pal and Foody, 2010). There have been no previous evaluations of the performance of these methods with GEOBIA, except a comparison of three unrepresentative feature selection methods reported by Laliberte et al. (2012). In the present study, we did not focus on the scale of the feature analysis. Instead, we simply employed the filtering algorithm CFS, which can select a feature subset using a correlation-based heuristic evaluation function (Hall et al., 2009), to obtain a subset of the best selected features (Pal and Foody, 2010).

GEOBIA must also overcome similar challenges to the traditional pixel-based approaches, such as the training set size and its completeness, where the image objects are initially extracted from an image (Pal and Mather, 2003; Congalton and Green, 2009; Hussain et al., 2013). It is essential that the number of classes is adequate for describing the land cover of the study area and the training data must provide a representative description of each class (Pal and Mather, 2003). For example, an important requirement of the ML classifier is that the number of pixels included in the training dataset for each class should be at least 10–30 times the number of features. Many previous studies have indicated that the size of the training dataset has a substantial effect on the classification accuracy (Pal and Mather, 2003; Foody et al., 2006). In traditional pixel-based classification analysis, there have been many analyses of the training set size (Van Niel et al., 2005; Foody et al., 2006; Rodriguez-Galiano et al., 2012), but few studies have addressed this issue for GEOBIA. For example, Zhen et al. (2013) investigated the effect of the training set size on the classification accuracy and the accuracy estimates obtained from the validation data, where the training and validation data were obtained from several selection schemes using WorldView-2 data. However, a key consideration is the deficiency of accuracy evaluation methods based on points, rather than area-based or polygon-based methods, as recommended recently, which may be a more reasonable evaluation method for segmented objects (Whiteside et al., 2014; Radoux and Bogaert, 2014). The accuracy assessment sample units may include single pixels, blocks, and polygons (Stehman and Wickham, 2011), but the accuracy assessment sample units should be polygons if the polygon map is created by manual interpretation, or using image segmentation and object-based classification algorithms (Congalton and Green, 2009). However, Zhen et al. (2013) failed to consider the effect of the training set size on the accuracy of classification using different segmentation scales. Thus, to make our results more robust, we analyzed the effect of the training set size on the classification accuracy, before using the classification accuracy to evaluate the scale. We also determined how the training set size affects the accuracy at different segmentation scales in GEOBIA.

In addition, civilian applications of Unmanned Aerial Vehicle (UAV) have increased considerably in recent years due to their great availability and because of the miniaturization of sensors, GPS, inertial measurement units, and other hardware (Zhou et al., 2009). UAV have been combined with remote sensing technology to acquire spatial data related to land cover, resources, and the environment for use in remote sensing data modeling and analysis processes (Cheng et al., 2008, 2012, 2014; Zhang and Kovacs, 2012; Ma et al., 2013a; Gomez-Candon et al., 2014). The high frequency and Very High Resolution (VHR) images obtained using UAV means that UAV have received increasing attention from researchers and manufacturers (Laliberte and Rango, 2009; Jaakkola et al., 2010; Kim et al., 2013; Ma et al., 2014; Lucieer et al., 2014). Thus, the