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Toward accountable land use mapping: Using geocomputation to improve classification accuracy and reveal uncertainty

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ABSTRACT

The classification of satellite imagery into land use/cover maps is a major challenge in the field of remote sensing. This research aimed at improving the classification accuracy while also revealing uncertain areas by employing a geocomputational approach. We computed numerous land use maps by considering both image texture and band ratio information in the classification procedure. For each land use class, those classifications with the highest class-accuracy were selected and combined into class-probability maps. By selecting the land use class with highest probability for each pixel, we created a hard classification. We stored the corresponding class probabilities in a separate map, indicating the spatial uncertainty in the hard classification. By combining the uncertainty map and the hard classification we created a probability-based land use map, containing spatial estimates of the uncertainty. The technique was tested for both ASTER and Landsat 5 satellite imagery of Gorizia, Italy, and resulted in a 34% and 31% increase, respectively, in the kappa coefficient of classification accuracy. We believe that geocomputational classification methods can be used generally to improve land use and land cover classification from imagery, and to help incorporate classification uncertainty into the resultant map themes.

1. Introduction

In studies of land use and land cover change, it has become commonplace to use remotely sensed data as the input, and to use classification and segmentation methods to derive land use/cover maps of the Earth's surface. Yet in spite of almost 30 years of experience, the quality of these maps is often judged as too low for operational applications (Foody, 2002). The growth of GIS has meant that maps derived from satellite imagery are frequently no longer an end product, but rather form inputs for further modelling and analysis. The further processing of these data can result in the propagation or amplification of classification errors (Heuvelink, 1998). Indeed, many geographic analyses become so open to error propagation that hard facts simply do not exist, and probabilistic and statistical methods become necessary (Comber et al., 2005).

Much research has focused on improving classification accuracy for land use/cover mapping using remotely sensed data. For an extensive overview of techniques to improve classification performance we refer to Lu and Weng (2007). Traditionally, most classification algorithms only use spectral information extracted from multispectral satellite imagery. In general, these classifiers are based on the premise that different land cover classes have a distinct spectral signature. The various reflectance values of each of the individual pixels are assigned to a class with the most similar spectral signature. These so-called per-pixel classifications (Lu and Weng, 2007) have been used extensively to classify satellite imagery with low to medium spatial resolution. At coarser spatial resolutions pixels more frequently consist of multiple mixed classes. This is a major problem for the 'hard' classification approaches, where a pixel can only be a member of one class. Different methods have been developed to create soft classifiers, where a pixel can belong to multiple classes (Lu and Weng, 2007).

With the introduction of high spatial resolution satellite imagery the impact of the mixed pixel problem has been reduced, as pixels are more likely to be a member of only one class. However, as the pixel size approaches the minimum size of elements within the class, the within-class spectral variance increases. This decreases spectral class separability and results in lower classification accuracy (Marceau et al., 1990; Shaban and Dikshit, 2001). In order to deal with high spectral within-class variation new classification approaches have been developed, such as the per-field, object-oriented and contextual classifiers (Lu and Weng, 2007). The per-field classifiers subdivide the image into

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fields or patches, which are subsequently used in the classification process instead of individual pixels (Aplin et al., 1999). The object-oriented classifiers are based on spectral and geometric properties of objects resulting from image segmentation (Benz et al., 2004). The contextual classifiers use the spatial relationship between one or more pixels with other pixels in the remainder of the scene to improve classification performance (Gurney and Townshend, 1983).

The spatial properties of the image can also be represented by a texture (Marceau et al., 1990). Texture differs from the contextual classifiers, as it describes the spatial variation in a contiguous group of pixels (Gurney and Townshend, 1983). Many researchers created new texture images to use as another feature or band in the classification process (e.g. Berberoglu et al., 2007; Franklin et al., 2000; Gong et al., 1992; Lu and Weng, 2005; Marceau et al., 1990; Puissant et al., 2005; Shaban and Dikshit, 2001; Wikantika, 2004). These studies show that the use of the Grey Level Co-occurrence Matrix (GLCM) has great potential for improving classification accuracy. Haralick et al. (1973) originally developed this successful texture measure. The GLCM contains the relative frequencies with which two pixels linked by a spatial relation (displacement vector) occur on a sliding window of the image (Pesaresi, 2000). The second order statistics derived from this matrix describe the texture of an image (Marceau et al., 1990). These textures can also be derived from first order statistics, i.e. statistics calculated from the image itself without considering pixel neighbour relationships (Hall-Beyer, 2007). Textures based on first order statistics can also improve classification performance (Ferro and Warner, 2002; Gong et al., 1992). Following Gong et al. (1992), these textures will be referred to as simple statistical transformations (SSTs). Use of GLCM and SST textures requires decisions concerning the spectral band, quantization level, texture statistic, size of the moving window and – for GLCM texture only – the displacement vector.

As there are numerous possible textures resulting from different variable settings, many studies have focused on finding optimal combinations of these variables. However, the results differ for each study. Recommendations for optimal window sizes vary from larger than 31×31 (Karathanassi et al., 2000), 17×17 or 25×25 pixels (Marceau et al., 1990) to 7×7 and 9×9 (Shaban and Dikshit, 2001) and to 5×5 (Gong et al., 1992). The most suitable statistic varies from homogeneity (Puissant et al., 2005) to standard deviation (Berberoglu et al., 2007) to the mean texture feature (Zhang et al., 2003). Finding the optimal texture features becomes even more complicated when multiple texture layers are added to the spectral bands. It is extremely difficult to predict which combinations of texture layers provide the best results. Various studies show that adding more than one texture layer in the classification process improves the results (Gong et al., 1992; Shaban and Dikshit, 2001; Zhang et al., 2003), but other studies argue that adding multiple texture layers does not significantly improve the results (Pesaresi, 2000; Wikantika, 2004).

It is not surprising that different studies deliver seemingly conflicting results, as the most suitable texture is dependent on various and *ad hoc* factors which differed throughout these studies. Factors like the spatial and spectral properties of the satellite imagery, the spatial patterns of the study area, the level of classification and the focus of the study – e.g. detection of urban object classes (Zhang, 1999) or improving the forest-age class separability (Franklin et al., 2001) – all contribute to the texture performance. As every image classification differs in at least one of these factors, it is impossible to find an optimal combination of texture layers that can be applied across different image classifications at different resolutions and for different instruments. Next to the derivation of texture layers, the spectral bands can also be combined as ratios to improve class separability (Helmer et al., 2000; Jensen, 2005).

This study proposes a geocomputational approach to improve the effectiveness of land use/cover mapping from remotely sensed data using texture and band ratio layers. Instead of limiting the number of possible layers based on the presumption that certain layers provide optimal classification results, our method tries out permutations of band ratios and texture layers recursively while optimizing a set of error measures. The numerous computations result in multiple accurate classifications, whose differences provide valuable information about the uncertainty in the classification method. We focus on two objectives:

Objective 1: increase classification accuracy;
Objective 2: include uncertainty information in the classified land use map.

2. Methods

2.1. Case study

The classified land use maps resulting from this research will be used as an addition to already existing land use maps. These maps were derived from the Coordination of Information on the Environment (CORINE) Land Cover (CLC) for dates 1990 and 2000. The CLC aims at providing consistent and up-to-date maps of European land cover (Bossard et al., 2000; CEC, 1994). In order to compare newly classified and CORINE maps, the classification scheme used was the same as that used for CORINE. Due to limited spatial resolution of especially Landsat satellite imagery and no real need for a more detailed classification, classification detail was limited to level 1 of the CORINE classification, resulting in the classes artificial, agriculture, natural, and water bodies. These classes are types of land use instead of land cover. This forms a challenge as satellite imagery is more suitable to create land cover maps, as spectral bands do not directly provide information about actual land use, e.g. a patch of trees can be a natural forest, an orchard or a park.

The proposed methodology was applied to satellite imagery covering a 23 km^2 large area around Gorizia, a small city on the Italian-Slovenian border at 45°95′N 13°62′E. The area has both hilly and flat areas with various landscapes and spatial patterns ranging from urban to rural to barren land. The region is being subjected to land use change modelling and a multi-temporal data set on land use was sought. We used a 2004 image from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and a 1991 image from the Landsat 5 Thematic Mapper (Landsat 5 TM), both provided and processed by the University of Trieste, Italy. Both the Landsat and ASTER-imagery were orthorectified to a 15 by 15 m grid to enable easy comparison.

2.2. Classification method

Primary inputs to the classification process were the spectral bands. First, texture or band ratio information was derived from the spectral bands and added as an additional layer. Multiple layers could be added in order to further improve classification accuracy. Then the study area was classified into *land cover* classes using maximum likelihood classification (MLC), as a type of land use often consists of different land cover elements which are easier to classify with satellite imagery (Wästfelt, 2009). In the post-classification the land cover classes were merged into CORINE level 1 land use classes. More advanced post-classification methods for combining land cover into land use exist, such as the spatial relational post-classification (Wästfelt, 2009), but are not the emphasis of this study and we did not pursue the matter further. Fig. 1 shows the classification method used to compute the land use maps, each time varying the additional layers.