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Enhancing the performance of regional land cover mapping

Weicheng Wu[a,*], Claudio Zucca[b], Fadi Karam[c], Guangping Liu[d]

[a] State-Key Lab of Nuclear Resources and Environment, East China Institute of Technology (ECIT), Nanchang, 330013 Jiangxi, China
[b] ICARDA (International Center for Agricultural Research Center in the Dry Areas), Amman, Jordan
[c] Litani River Authority, Beirut, Lebanon
[d] Faculty of Sciences, East China Institute of Technology (ECIT), 330013, Nanchang, Jiangxi, China

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ABSTRACT

Different pixel-based, object-based and subpixel-based methods such as time-series analysis, decision-tree, and different supervised approaches have been proposed to conduct land use/cover classification. However, despite their proven advantages in small dataset tests, their performance is variable and less satisfactory while dealing with large datasets, particularly, for regional-scale mapping with high resolution data due to the complexity and diversity in landscapes and land cover patterns, and the unacceptably long processing time. The objective of this paper is to demonstrate the comparatively highest performance of an operational approach based on integration of multisource information ensuring high mapping accuracy in large areas with acceptable processing time. The information used includes phenologically contrasted multiseasonal and multispectral bands, vegetation index, land surface temperature, and topographic features. The performance of different conventional and machine learning classifiers namely Malahanobis Distance (MD), Maximum Likelihood (ML), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Random Forests (RFs) was compared using the same datasets in the same IDL (Interactive Data Language) environment. An Eastern Mediterranean area with complex landscape and steep climate gradients was selected to test and develop the operational approach. The results showed that SVMs and RFs classifiers produced most accurate mapping at local-scale (up to 96.85% in Overall Accuracy), but were very time-consuming in whole-scene classification (more than five days per scene) whereas ML fulfilled the task rapidly (about 10 min per scene) with satisfying accuracy (94.2–96.4%). Thus, the approach composed of integration of seasonally contrasted multisource data and sampling at subclass level followed by a ML classification is a suitable candidate to become an operational and effective regional land cover mapping method.

1. Introduction

Land cover (LC) and land use (LU) data are fundamental inputs for a wide range of environmental planning, management and research applications. Nowadays, LC mapping mostly relies on remote sensing building on more than 40 years of scientific research and technological developments from local to global scale (Atkinson and Tatnall, 1997; Chen et al., 2015; DeFries et al., 1998; Friedl et al., 2002; Gong et al., 1992, 2013; Hansen et al., 2000; Haralick et al., 1973; Wu and Zhang, 2003; Wu et al., 2013a). However, accuracy and reliability may become a challenge when using high resolution data for regional and global mapping. For example, as reported by Gong et al. (2013) concerning their global LC mapping using Landsat data, the Overall Accuracies (OAs) were below 70% for all continental-scale and below 75% for most national-scale maps except for some countries like Algeria, Saudi Arabia, Libya where LC patterns are simple.

The conventional classification approaches adopted pattern recognition techniques including both supervised and unsupervised algorithms, assuming that the study area is composed of a number of unique internally homogenous classes that are mutually exclusive (Townshend, 1984). However, such assumption is not applicable to most natural or semi-natural areas where there are mixed pixels (Adams et al., 1995; Atkinson, 2005; Hill and Schutt, 2000; Van Der Meer, 1995), and especially LC types exist as continua rather than as a mosaic of discrete classes (Foody et al., 1992; Kent et al., 1997; Wu and Zhang, 2003). As a result, the classes intergrade showing a low degree of separability, and cannot be distinguished by means of sharp boundaries (Foody et al., 1992). The separability of classes can be evaluated by the Jeffreys-Matusita Distance (JMD)

* Corresponding author.
E-mail addresses: Wuwc123@gmail.com, wchwu@ecit.cn (W. Wu).

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according to Swain and King (1973) and Richards and Jia (2006). For the pair of classes i and j, this distance can be expressed as:

$$JMD_{ij} = 2(1 - e^{-\alpha}) \tag{1}$$

where

$$\alpha = \frac{1}{8}\left(\mu_i - \mu_j\right)^T\left((C_i + C_j)/2\right)^{-1}\left(\mu_i - \mu_j\right) + \frac{1}{2}\ln\left[\left(\frac{1}{2}|C_i + C_j|\right)/\sqrt{|C_i| \times |C_j|}\right] \tag{2}$$

C_i—the covariance matrix of class i; μ_i—the mean vector of class i; ln—the natural logarithm function; T—the transposition function; and $|C_i|$—the determinant of C_i; the same meanings for the counterparts of class j. JMD ranges from 0 to 2.0; when it is below 1.0, two classes (of a class-pair) are not separable; when it is between 1.0 and 1.5, two classes are separable but with confusion, and when it is between 1.5 and 1.9, two classes are clearly separable; only when JMD is above 1.9 the class-pair is completely separable.

For poorly separable classes the accuracy of classification is the major problem in LC mapping. For this purpose, a number of authors have explored the possibility to improve mapping accuracy by taking into account the texture (Gong et al., 1992; Haralick et al., 1973; Zhang, 2001) or by object-based segmentation (Mao and Jain, 1992; Blaschke, 2010; Pu et al., 2011) or by combining both pixel- and object-based approaches (Huth et al., 2012; Chen et al., 2015). In addition to the traditional unsupervised (e.g., IsoData, K-Means) and supervised algorithms, e.g., Mahalanobis Distance (MD) and Maximum Likelihood (ML), a number of authors have introduced machine learning algorithms that can capture the non-parametric signatures of classes such as Artificial Neural Networks (ANNs, Atkinson and Tatnall, 1997; Benediktsson et al., 1990; Kavzoglu and Mather, 2003), Support Vector Machines (SVMs, Foody and Mathur, 2004; Huang et al., 2002; Kavzoglu and Colkesen, 2009; Vapnik and Lerner, 1963) and Random Forests (RFs, Breiman, 2001; Rodriguez-Galiano et al., 2012; Waske et al., 2012).

For mixed pixels, various subpixel processing techniques have been proposed to decompose land cover fraction or to improve LC mapping accuracy, e.g., linear spectral unmixing (Adams et al., 1986; Foody and Cox, 1994; Hill and Schutt, 2000; Lu and Weng, 2004; Smith et al., 1990; Van Der Meer, 1995), linear optimization (Verhoeye and De Wulf, 2002), Hopfield neural network (Tatem et al., 2002), pixel-swapping (Atkinson, 2005), subpixel/pixel attraction (Mertens et al., 2006), etc.

Some authors have also integrated a set of single or time-series vegetation indices (VIs) such as NDVI (Normalized Difference Vegetation Index) or EVI (Enhanced Vegetation Index) and land surface temperature (LST) to undertake LC mapping (Friedl et al., 2002; Loveland et al., 2000; Lu et al., 2014). Furthermore, topographic features have been employed in LC classification to improve accuracy (Benediktsson et al., 1990; Rodriguez-Galiano et al., 2012), particularly by the ESA-funded DesertWatch project (Pace et al., 2006; ESA, 2008), based on the assumption that landscape features restrain to a certain extent land use or land cover. For example, irrigated land generally occurs in flat to gently sloping land. Phenological patterns and features (Zhu and Wan, 1963) have also played a role in LC mapping (Friedl et al., 2002; Jia et al., 2014; Lu et al., 2014). The above mentioned DesertWatch project and Rodriguez-Galiano et al. (2012) used paired season-contrasted spring and summer images instead of time-series data to enhance LC classification.

The goal of this research is to demonstrate the performance of a LC mapping procedure based on the integrated use of the phenology-contrasted information including multispectral (MS) bands of images, GDVI (Generalized Difference Vegetation Index) which is more sensitive than other VIs for dryland characterization (Wu, 2014), LST, and topographic features extracted from a Digital Elevation Model (DEM), and to compare it with that of some other widely adopted supervised approaches. The specific objective is to quantify the achieved improvement in terms of separability of classes, accuracy of the classification, and processing time by integration of multisource high resolution data for area with complex landscape.

2. Data and methods

2.1. Study area

The study area is located in the Eastern Mediterranean Region and coincides with the area covered by Landsat scenes with path/row numbers of 174/35–174/37 (Fig. 1). This area was chosen because it is a dryland characterized by steep climatic gradients with various landforms and complex LC patterns, thus a challenging site for remote sensing-based LC mapping. Two subset sites with contrasting LC and LU characteristics were also defined (Fig. 1) for experimental purposes as explained below.

In the study area rainfall is mostly concentrated between November and April and ranges from around 650 mm on the western coastal slopes to less than 100 mm in the eastern dry rangelands and deserts. Three main landforms are respectively, from the west to the east, the coastal plains and piedmont, the mountain–valley–mountain sequence of the north-south stretching coastal ranges, and the eastern plateau. Natural vegetation cover mainly consists of coniferous and broadleaf forests in the highlands, shrublands and maquis in the mountain slopes, and herbaceous rangelands in the eastern hills and plateau (Wu, 2014).

Irrigation is mainly concentrated in the Aleppo Plain, Orontes and Litani watersheds and Jordan River valley. The main spring crops are irrigated wheat and vegetables, and rainfed barley, whereas summer crops are irrigated cotton, maize, sunflower, sesame, water melon and vegetables. Olive is widespread in rainfed areas, interleaved with fig and pistachio. Orchards including citrus, apple, cherry, peach, etc., are mainly distributed in the western coastal plains and slopes. Date, banana and vineyards are mostly present in the Bekaa and Jordan River valleys. The major land use/cover classes of the study area are summarized in Table 1.

In Table 1 the category "Conifers" does not only include monospecific pine and/or cedar stands, but also mixed formations including broadleaved species. The distinction between forests (Conifers and Broadleaf) and "Woodland" or "Woody Shrubland", is based on the FAO Land Cover Classification System (LCCS, Di Gregorio and Jansen, 2000): forests have tree canopy cover (CC) above 60%, whereas CC is between 20 and 60% for woodlands and less than 20% for sparse woodlands (Wu et al., 2013b). Since sparse woody formations are generally used as grazing land in the study area, this class was considered as part of the "Rangelands".

2.2. Data

Landsat 5 TM (Thematic Mapper) spring (01 May 2007) and summer (21 August 2007) images were acquired for the scene 174/35. Landsat 8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) data were obtained for the scenes 174/36 (02 April 2014 and 24 August 2014) and 174/37 (18 April 2014 and 24 August 2014). The two dates represent respectively the spring vegetative maximum and the summer minimum, they are thus highly contrasted. Extensive ground-truthing work was conducted in the period 2007–2011 in Syria and in 2013–2014 in Lebanon and Jordan (GPS locations in Fig. 1). Google Earth was used as a complementary source for areas not covered by field work. SRTM (Shuttle Radar Topography Mission) DEM data (90 m in resolution) were obtained and used to generate elevation (E), slope (S), and aspect (A) information.