LANDCOVER CHANGE DETECTION USING GIS AND REMOTE SENSING TECHNIQUES

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Abstract: Nowadays important tools for monitoring and managing resources are remotely sensed data. Remote sensing change detection can be used to discern and simulate areas that have been altered by natural or anthropogenic processes (Jantz, Goetz, & Shelley, 2004; Hansen, & Rotella, 2002; Wang et al., 2009). High quality monitoring of environment is mandatory not only for nature values conservation but also for cultural and traditional heritage protection. The most common technique used in this process is imagery classification, supervised and post-PCA unsupervised. The supervised classification is user - guided classification where training samples and class number determine user, and samples are used to generate classification statistics (mean; variance/covariance). With post-PCA unsupervised classification can be identified groups of possible changes represented by different classes, can be identified land cover change classes and their size can be determined. Understanding of Land Cover (LC) changes is fundamental in order to establish and understand relations and interactions between humans and the natural environment, where applying new methodologies of remote sensing and geographic information systems (GIS) have special role in obtaining high quality information.
Keywords: land cover change, remote sensing, classification, GIS environment

INTRODUCTION

Both natural processes and anthropogenic activities have great influence on vegetation cover causing the changes. In that sense, global environmental monitoring is necessary. Regarding the availability of remotely sensed time series data of more or less entire surface global monitoring of the Earth is possible. Whole Earth can be sensed and changes on the earth's surface can be monitored consistently and in a synoptic way (Eastman et al, 2013; Osunmadewa, Csaplovics, Majdaldin, Adeofun, & Aralova, 2017). Remotely sensed data are well established as valuable sources of information for not only stakeholders and natural resource managers but for all people interested in change detection monitoring. Nowadays, big data archives, due to the multi-decadal historical records accumulation, implementation of new sensors, together with analytical techniques development provide a good basis for rapid expansion of the remotely sensed data application.

Time series of images are often used to analyze landscape-scale changes of natural resources, while data from high-resolution sensors can be used to detect and quantify small changes in topography, to map plant species or even individual plants, or measure flows of nutrients and energy that alter plant growth and affect fire risk (Gross, Nemani, Turner, & Melton, 2006). Remote sensing (RS) is a proven technology for effective mapping and characterizing cultural and natural resources (Wang, 2011) with a broad application for change detection analysis. In order to create a better understanding of the rapid advancements in remote sensing technology numerous reviews of the current state of remote sensing technology (i.e. sensors, data, analysis methods and applications) for monitoring land cover and land use were done.

Land-use types in a long term can affect the natural landscape, ecosystems, plants communities, water flows and local climate at regional level. Understanding how land use and land cover have affected regional landscape configuration and composition can provide a historical framework for measuring associated changes in ecosystem function and can be used to guide restoration where desirable and feasible (Wilkinson, Parker & Evans, 2008; Wang et al., 2009). Knowledge of historical trends of land-cover change, not only how much has changed but also where and when changes have occurred, can help land managers to identify key resource and ecosystem stressors, as well as prioritize management efforts (Shriver et al., 2005; Wang et al., 2009).

REMOTE SENSING IN LAND COVER CHANGES

In the last three decades, the technologies and methods of RS have evolved dramatically to include a suite of sensors operating at a wide range of imaging scales with potential interest and importance to planners and land managers (Rogan & Chen 2004). The reduction in data cost and increased resolution from satellite platforms together with the ready availability of historical remote sensing data, resulted in acceptance of remote sensing technology as one of the best for monitoring changes in nature.

Current remote sensing technology offers collection and analysis of data from ground-based, atmospheric, and Earth-orbiting platforms, with linkages to GPS data, GIS data layers and functions, and emerging modelling capabilities (Franklin, 2001; Rogan & Chen, 2004). This has made RS a valuable source of land-cover and land-use information together with its wide use of planning agencies and in land management initiatives for monitoring land-cover and land-use change at a variety of spatial scales. Change detection has often been discussed in the literature by numerous authors.

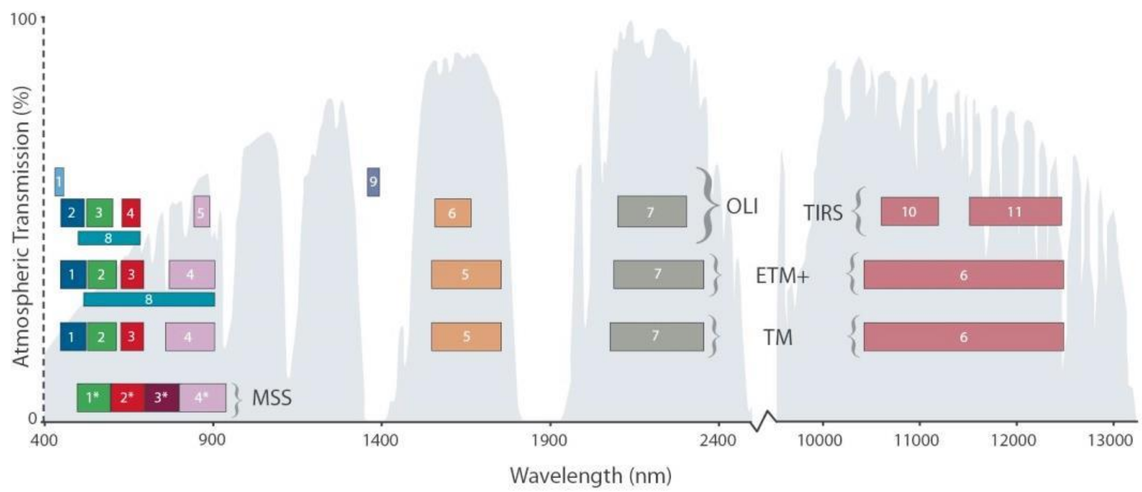
Those types of human-induced land-cover change transform natural habitats and pose the single most important threat to biodiversity (Wessels et al., 2004; Sala et al., 2000; Soule, 1991; Wang et al., 2009). Several recent reviews document the broad range of applications of remotely sensed data to support conservation of biodiversity and ecosystem management, and to evaluate broader issues of land use change (Kerr and Ostrovsky 2003; Turner, Spector, Gardiner, Fladeland, Sterling, & Steininger, 2003; Hansen, De Fries, & Turner, 2004; Gros et al., 2006). Applications of some of data, obtained by remote sensing technology, can directly support monitoring and management needs in units of the protected areas systems, including high-priority areas of monitoring landscape dynamics, invasive species, forest fires and other disturbances.

Change detection studies involve a series of sequential steps that are detailed extensively elsewhere (e.g. Cihlar, 2000; Coops et al., 2007; Lunetta, 1998; Schott, 1997), and it is important for the natural resource manager to understand it well.

Kennedy et al. (2009) identify four main but broad steps of change detection of vegetation cover and simplified them to data acquisition, pre-processing and/or enhancement, analysis and evaluation.

The first problem in change detection is to acquire a pair of images separated by a suitable time period. Also, image dataset quality depends on a type of sensor involved in detection (Fig. 1).

Figure 1. Difference between Landsat sensors, USGS (2017).



* MSS bands 1–4 were known as bands 4–7, respectively, on Landsats 1–3

Differences between two image sets of the same area may reflect seasonal changes, changes due to antecedent weather conditions and apparent changes that are introduced by differences in sensor calibration, atmospheric effects and viewing/illumination geometry (Mather & Koch, 2011). That is the reason why pre-procession of the raw dataset should be involved. Some methods as ones based on correlations do not need correction for atmospheric path radiance as the means of all the image bands are set to zero; however, absorption and other effects are not accounted for.

For LC change analysis many methodologies are being developed and used, for e.g. traditional post-classification cross tabulation, cross correlation analysis, neural networks, knowledge-based expert systems and image segmentation and object-oriented classification (Rawat & Kumar, 2015).

METHODOLOGY REVIEW

Over the last two decades numerous investigation of land changes have been done using developed and evaluated methodologies (Rogan, Franklin & Roberts, 2002; Woodcock & Ozdogan, 2004; Healey, Cohen, Zhiqiang, &

Krankina, 2005; Wang et al., 2009). As an example, study of El Gammal et al. (2010) can be taken. Authors used several Landsat images of different time periods and processed them in ERDAS and Arc-GIS softwares to determine changes.

The most common types of classification of imagery are supervised and post-PCA unsupervised classification. Both methodologies are used for detecting LC changes for e.g. Fichera, Modica and Polino (2012) used supervised classification while Deng, Wang, Deng, and Qi (2008) used PCA based unsupervised classification.

Supervised classification

Supervised classification is learning method for establishing classification from a training dataset, which contains the predictor variables measured in each sampling unit and assigns prior classes to the sampling units (Černá & Chytrý, 2005; Xie, Sha & Yu, 2008). Training areas were selected to support the supervised classification algorithm using the Maximum Likelihood Classification (MLC) rule that is the most accurate of the classifiers in the ERDAS, because it takes the most variables into account (Hong, MacGillavry, Raaphorst, 1998). Based on it a Bayesian Probability Function is calculated from the inputs for classes established from training sites. Each pixel is then assigned to the class to which it most probably belongs (Short, 2007; Macalister & Mahaxay, 2009).

The most common way to represent the classification accuracy of remotely sensed data, recommended by many researchers, is in the form of an error matrix. The accuracy matrices compare the classification output (by pixels within delineated polygons) to the actual land cover (determined for points within polygons). It is also used as a starting point for a series of descriptive and analytical statistical techniques (Congalton, 1991).

Post-PCA unsupervised classification

The principal component analysis (PCA) is based on the fact that neighboring bands of hyperspectral images are highly correlated and often convey almost the same information about the object. This analysis combines all correlated information in the same PC and if reflectance stays the same between different dates for the same pixel, it is expected that this pixel will have a high value in the 1st and/or 2nd PC and low in the other PCs. When the reflectance changes, it is expect that all pixels shows high values in subsequent PCs (2nd and 3rd onwards). PCA approach can effectively ensure a practically acceptable and accurate classification result by handling only a small data set (5-10 %) derived from the original large amount of image data.

Unsupervised classification is a method in which the computer searches for natural groupings of similar pixels called cluster and user only defines the number of clusters. In ERDAS unsupervised classification is performed using an algorithm called the Iterative Self-Organizing Data Analysis Technique (ISODATA) and defining the desired number of clusters and a confidence threshold. Then clusters are built iteratively, meaning that with each new iteration the clusters become more and more refined. The iterations stop when the confidence level (or a maximum number of iterations specified by the user) is reached. After the clusters are built, selection of the land cover classes is done by the analyst, assigning the each cluster to the appropriate class.

The problem with unsupervised PCA based classification is that misclassified pixels mainly occur at feature borders or edges. The border effect is due to the loss of information or contrast in the process of transformation, such that the boarder becomes “smoothed” or less contrasted in the PCA band images. This misclassification does not change the general class patterns and, therefore, the dominating classification results still remain correct. It is important to notice that misclassifications caused by PCA-induced information loss mainly occur at feature class borders in the image and are more sensitive for rural areas (Rodarmel & Shan, 2002).

Mather & Koch (1999) presented a comprehensive and detailed summary of different applications of PCA, including correlation analysis of Landsat TM images for effective feature recognition and identification of areas of change with multitemporal images (Rodarmel & Shan, 2002).

CONSLUSION

The only limitation of wide application of RS data and GIS analysis is necessity of experts from the fields of GIS and Remote Sensing who can provide to a manager wanted results. According to (Kennedy et al., 2009) resource managers must specialize their capabilities of an ever-expanding array of image sources and analysis techniques in order to understand changes.

Understanding of Land Cover (LC) changes is fundamental in order to establish and understand the relations and interactions between humans and the natural environment. Changes in land cover by land use do not necessarily imply degradation of the land but some of them can have positive effect on environment. However, many shifting land use patterns driven by a variety of social causes, result in land cover changes that affects biosphere in global and its understanding is of importance.

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