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Pixel Based and Object Based Fuzzy LULC Classification using GRASS GIS and RapidEye Imagery of Lao Cai Area, Vietnam

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1. Introduction

Remote sensing data is valuable source to extract LULC information. RapidEye image – a high resolution optical remotely sensed imagery with red-edge channel which can improve LULC classification (Schuster *et al.,* 2012). The fuzzy method which defines soft boundaries dividing LULC objects has been applied successfully by many authors (Zhang & Foody, 2010). In this study, fuzzy LULC classification has approached at both pixel and object level for Lao Cai area, Vietnam where there are both urban, sub-urban and forest land cover exist.

2. Data and methodology

2.1. Data and Study area

The study area is located in Lao Cai province, the mountainous area in the north of Vietnam. Main LULC classes in the area are: built-up (urban, road, mining activity area), water, baresoil, agriculture and vegetation (shrub, plantation, forest). The remotely sensed data used is RapidEye multispectral Level 3A dataset acquired on September 2014 covering the study area.

Reference data has collected from forest map in scale 1:10000 (Ministry of Agriculture & Rural Development, Vietnam) in order to be used as training data for classification and data for accuracy assessment.

2.2. Methodology

A small part of the RapidEye image covered by cloud has been removed, so the study area is completely cloud-free. Atmospheric correction and terrain correction has been carried out as preprocessing to remove or reduce the influence of atmospheric and topographic shadow effects. After pre-processing, fuzzy classification is applied at pixel level and object level. Flow chart of the methodology has been shown in Fig. 1.

2.2.1. Pre-processing

The study area includes mountainous area so it is necessary to remove noises affected by both atmospheric and topographic shadow effect. Atmospheric correction is done by calculating Top of Atmosphere (ToA); topographic correction has been effectively carried out by GRASS GIS module "i.topo.corr".

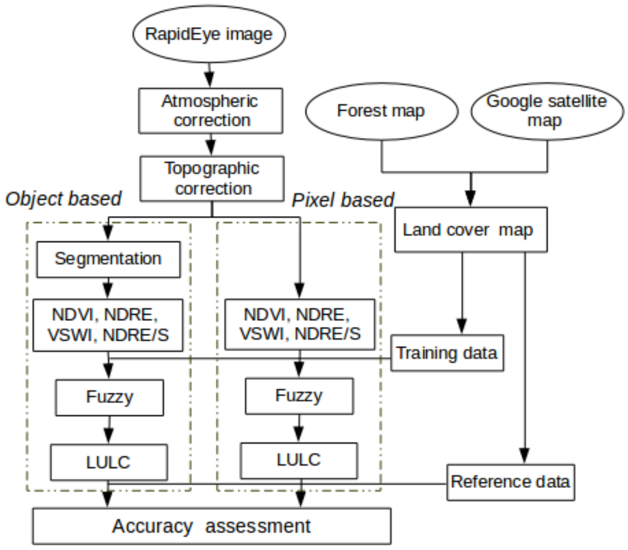

Fig. 1. Flow chart of fuzzy LULC classification

2.2.2. Fuzzy classification

As Zedeh mentioned: "Fuzzy logic aims at modeling the imprecise modes of reasoning that play an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision". The basic idea of fuzzy logic is that a propostion p is a collection of elastic constrains, C_1, …, C_k, which restrict the values of variables $X = (X_1, \ldots, X_n)$. This is accomplished by representing p:

$$p \rightarrow X \text{ is } A$$

in which A is a fuzzy predicate. An n-array fuzzy relation in U: $U = U_1 \times U_2 \times \ldots \times U_n$, and U_i, i = 1, …, n is the domain of X_i. P implies that the possibility distribution of X is equal to A:

$$\pi_X = A$$

which in turn implies that:

$$\mathrm{Poss}\{X = u\} = \mu_A(u),\ u \in U$$

Where μ_A is the membership function of A and Poss{X = u} is the possibility that X may take u as its value (Zedeh, 1988).

Fuzzy classification is Fuzzy Rule-based system in Fuzzy logic in which input has to be transformed into fuzzy statements (fuzzy sets). The input conjointly the fuzzy sets of rule base is caculated in the computational unit, which return again fuzzy sets as output. The process to transform from input to fuzzy sets called "fuzzification", and the process transform from fuzzy sets to output named "defuzzification".

2.2.3. Pixel based fuzzy classification

Vegetation-Soil-Water Index (VSWI) includes Soil index (S), Water index (W), Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE) and NDRE Soil index ratio (NDRE/S) have been used as rule based input data for fuzzy analysis.

Full fuzzy logic standalone classification system "i.fuzzy.system" in GRASS GIS has been used to generate the LULC map.

2.2.4. Object based fuzzy classification

Image objects are extracted from an image or group of images to individualsegments based on gray tone, shape, etc. Segmented image has been created by using "i.segment" module in GRASS. Object basedIndex maps: VSWI, NDVI, NDRE are generated from segmented spectral bands.

3. Result and Discussions

Fig. 2 and Fig. 3 are showing the classified maps by pixel based and object based fuzzy classification respectively. Five classes: water, built-up, agriculture, vegetation, baresoil have been demarcated by both pixel based and object based classification. Accuracy assessment has been carried out by comparing with reference sample andthe result of the accuracy assessment has shown in Table 1. Even though, over all accuracy of pixel based classification shows better result with accuracy of 72.25% compared with value 65.36% of object based, some classes (bare soil, agriculture) are showing poor result. Especially, accuracy of agriculture class is very low in both pixel based and object base classification, only 38.55% and 44.58% respectively, because of similar spectral characteristic of the class and vegetation. Fluctuation in determining rules for fuzzy also can be reason for low accuracy in those classes.

4. Conclusion and future work

In this paper, we examined performance of fuzzy classification both in pixel based and object based methods. Comparative evaluation shows that both methods are performing better some classes which other cannot present well. Therefore, the selective combination/ fusion of both object based and pixel based fuzzy classification could produce high accuracy results. In the future work study will focus to improve the fuzzy classification by combining object based pixel based classification by Dempster-Shafer Theory of Evidence (Shafer, 1976). Further also determination of rules for fuzzy also can be improved collecting better field data.

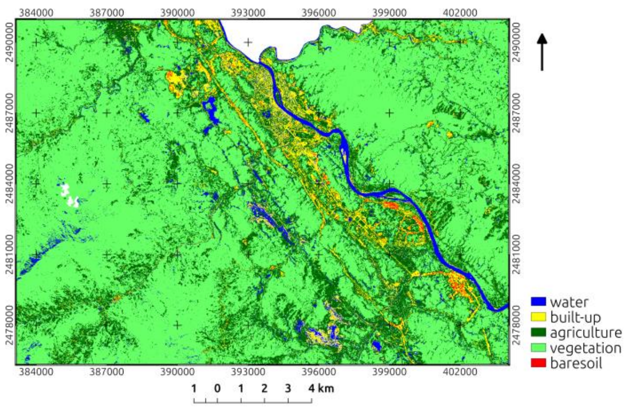

Fig. 2. LULC pixel based classification.

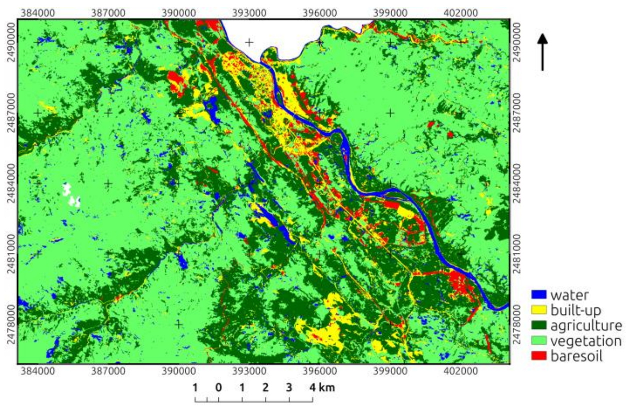

Fig. 3. LULC object based classification.

Table 1. Accuracy of Pixel based and Object based LULC classification in percentage

	Water (%)	Built-up (%)	Agriculture (%)	Vegetation (%)	Baresoil (%)	**Total** (%)
Pixel based	82.04	74.66	38.55	87.09	47.15	**72.55**
Object based	74.17	59.18	44.58	73.20	97.72	**65.36**

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