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COMBINING PIXEL-BASED AND OBJECT-BASED FUZZY CLASSIFICATION FOR LULC MAPPING USING SPECTRAL INDICES OF RAPID EYE IMAGERY AND FOSS4G

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Abstract

In this study, a combined of pixel based and object-based fuzzy approach for land use/ land cover (LULC) classification from RapidEye imagery is presented. The fuzzy pixel-based classifier utilizes Normalize difference vegetation index (NDVI) to discriminate water, non-water and vegetation land cover classes. After the pixel-based classification, segmented image was applied for both non-water and vegetation classes. Object-based fuzzy classification uses Soil index (SI) which extracted from Vegetation -Soil-Water index (VSW) to identify water, soil, built-up, agriculture and vegetation classes from non-water class. Vegetation class extracted from pixel-based classification was merged with vegetation class extracted from non-water class and object-based fuzzy classification was applied for Normalize difference Red-edge index (NDRE), NDRE/SI ratio and Digital Elevation Model (DEM) of the class to separate agriculture and forest classes. The process of this study was performed by using GRASS, one of Free Open Source Software for Geospatial (FOSS4G). Combining pixel-based and object-based fuzzy classifier is capable of identifying five main LULC classes with 85.7 % classification accuracy.

Keywords:Fuzzy, LULC, FOSS4G, Object-based, Pixel-based, Spectral indices, GRASS

1. Introduction

Information about LULC is important for natural disaster monitoring, management decision-making, urban planning (Trincsi, 2014). In Lao Cai area which located in Lao Cai - a mountainous province in the north of Vietnam, human activity and natural hazards lead to change of LULC time by time, so it is necessary to update new LULC situation.

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, 2012).

Various mixed LULC classes can be exists in present remote sensing data which causes due to existence of pixels or objects that belongs to two or more LULC classes (Bardossy, 2002; Melgani, 2000). Recently, several methods have been developed for LULC classification from remote sensing data to derive high accuracy land cover maps by resolving mixed pixels problem (Boyd, 2011). Fuzzy classification techniques allow solving the mix problem. Object-based classification leads to overcome salt-and-pepper effect, it is useful to analyze image as objects instead of using pixel-based classification unit (Yu, 2006).

As Steiniger (2012) mentioned; the first letter “F” of FOSS4G means freedom: Freedom to run, study and adapt the software for own needs, redistribute, improve the software and release the improvements to the public. FOSS4G includes Desktop GIS, Spatial Data Base Management Systems (Spatial DBMSs), GIS Server and geoprocessing on the Cloud, Mobile GIS, Remote sensing software, GIS extensions, plug-ins, APIs and so on. It strongly supports various aspects related to spatial data. Geographic Resources Analysis Support System (GRASS, or GRASS GIS) is desktop GIS software which is useful for geospatial data management and analysis, image processing, graphics and maps production, spatial modeling, and visualization.

Spectral indices such as vegetation index, water index and soil index are widely used in LULC classification using remotely sensed data due to the competency in highlighting individual objects. NDVI, NDRE are used to recognize vegetation and NDWI for separating water class while SI can be used to differentiate soil based on the distance between a pixel to soil line.

Using pixel-based or object-based Fuzzy LULC classification method individually does not perform a high accuracy for all LULC classes hence combination of both pixel-based and object-based classification obtains a comparatively high accuracy in classification results (Do, 2016). In this study, LULC of Lao Cai area is extracted by applying fuzzy system classification for spectral indices by comparing both pixel-based and object-based classification.

2. Data

The remotely sensed data was used for this study which is acquired on 9th September 2014 by RapidEye satellite covering around 32 km^2 of Lao Cai area where main land cover classes are: built-up (urban, road, mining activity area), water, bare soil, agriculture and forest (shrub, forest). RapidEye imagery is optical multispectral imagery with five distinct bands: Blue (440 nm – 510 nm), Green (520 – 590 nm), Red (630 – 685 nm), Red Edge (690 – 730 nm) – the band which is sensitive to changes in chlorophyll content and NIR (760 – 850 nm). The image used is level 3A with radiometric, geometric and terrain corrections with a resolution of 5 meters.

DEM 10 meters interval resolution data is collected from Topographic map in scale 1:10000 (Ministry of Natural Resources & Environment).

Reference was developed by combining forest map in scale 1:10000 (Ministry of Agriculture & Rural Development, Vietnam) and Google Satellite image where polygons of training and reference data are collected. Total 4748 pixels of these polygons were used as training sample and other 68229 pixels were used for accuracy assessment.

3. Methodology

Objects are created by grouping pixels (segment image) which have similar digital values, and possesses an intrinsic size, shape, and geographic relationship with the imprecise nature of the data (Hay, 2001). Accuracy of object-based classification is strongly affected by the quality of the image segmentation (Shackelford, 2003), while applying segmentation for all the study area is not get accurate result because of difference in size and shape of several of LULC classes. Accordingly, classes of LULC: vegetation (includes agriculture and forest), non-water (includes soil, built-up, agriculture and vegetation) and water were indentified. Later, segmentation is applied for vegetation and non-water class using *“i.segment”* module in GRASS.

Jhang (2001) highlights some reasons lead to mix of more than one LULC class in pixel unit. To solve this problem, there are several soft-classifier approaches which take these uncertainties into account; one of them is fuzzy classification which can describe the multiple and partial class membership properties of mixed pixels (Foody, 1996).The degree of uncertainty for each object is shown in fuzzy classification result as the percentage of the objects (Benz, 1999). Main concepts of Fuzzy classification are: Fuzzy logic which shows the degree of truth ranges between 0 and 1 (membership); Fuzzy set which includes boundary to define grade membership of data, and Fuzzy rule to shows relationship between input and output of the classification.

Fuzzy system classification is Fuzzy Rule-based system in which input has to be transformed into fuzzy statements (fuzzy sets). The input conjointly the fuzzy sets of rule base is calculated 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*”. Full fuzzy logic standalone classification system “*i.fuzzy.system*” in GRASS has been used to generate the LULC map. Shape of input fuzzy sets is “*s-shaped*” and of all output fuzzy sets are “*linear*”. Flow chart of the methodology is shown in Fig. 1.

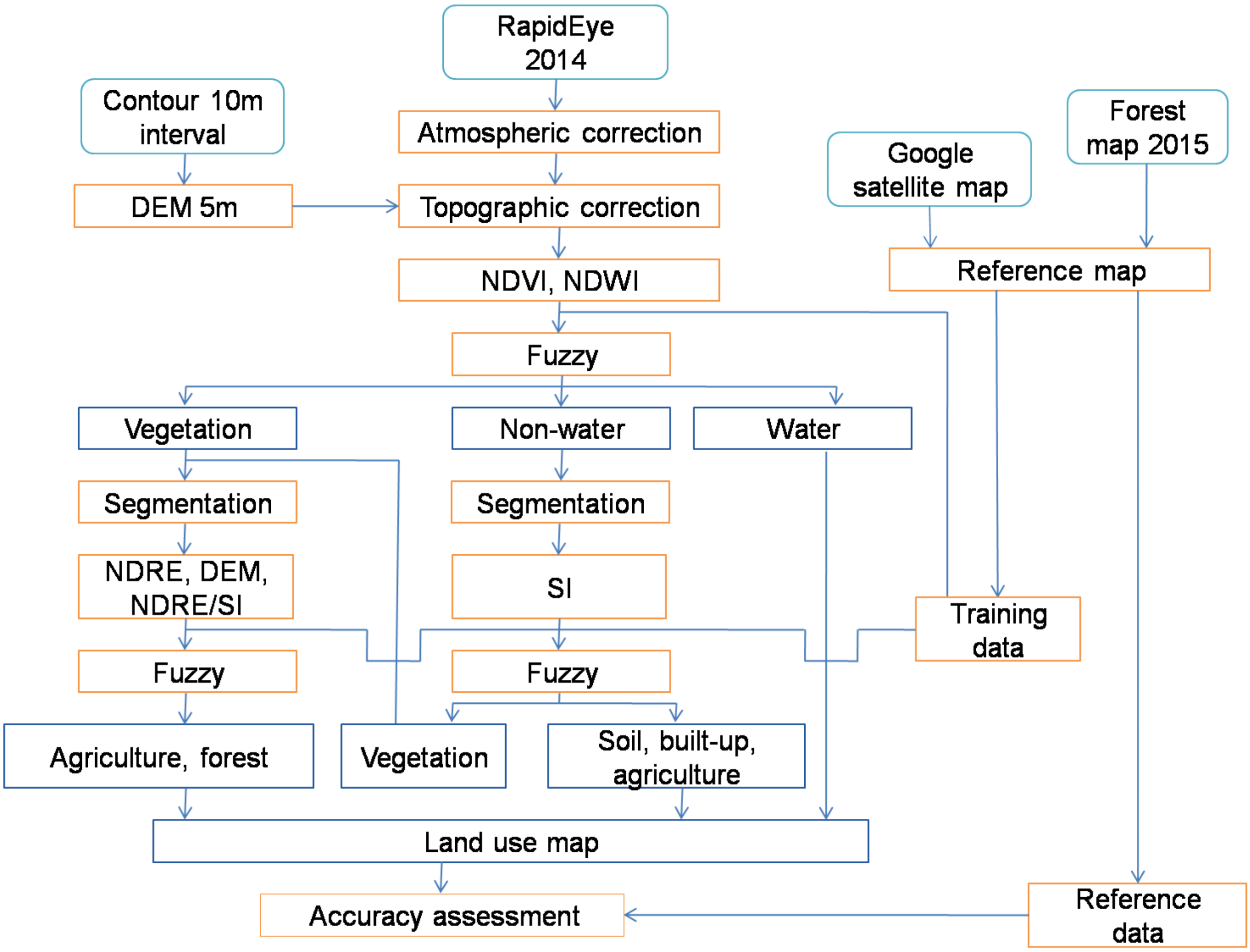

Fig. 1. Flowchart of methodology

3.1. Pre-processing

It is necessary to remove noises affected by both atmospheric and topographic shadow effect since the study area includes mountainous areas. Atmospheric correction is done by calculating Top of Atmosphere (ToA) radiance; topographic correction has been effectively carried out by computing the ToA reflectance.

3.2. Pixel-based fuzzy classification

In pixel-based classifier, NDVI and NDWI are used for fuzzy system classification to extract water class, non-water and vegetation class. Because part of agriculture and forest spectral are similar to built-up and soil, non-water class includes soil, built-up, agriculture and vegetation classes while vegetation class has agriculture and forest classes. Setting up membership is based on spectral characteristic of training sample. Rules for classification are expressed by:

If NDVI = high *and* NDWI = low *then* Class = vegetation
If NDWI = high *then* Class = water
If other cases *then* Class = non-water

Fig. 2 shows the value of classification output corresponding to percentage of the output classes in each pixel. Based on the percentage value, the three classes are extracted (Fig. 3).

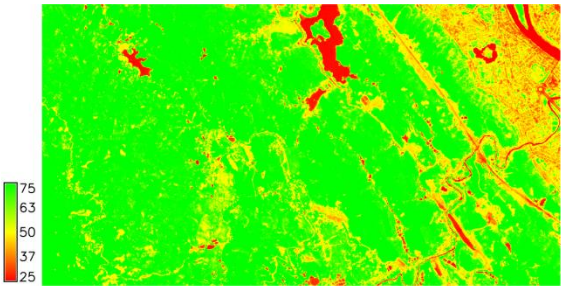

Fig. 2. Pixel-based classification output

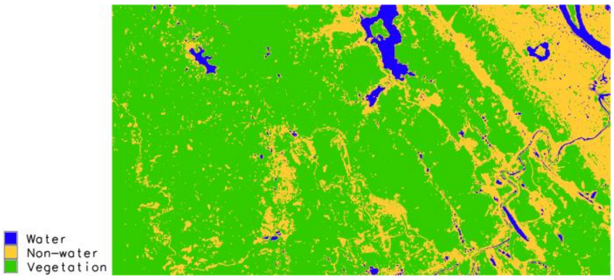

Fig. 3. Map showing three LULC classes

3.3. Segmentation

Water is end classification class while the two classes need re-classify because of the existence of more than one LULC classes inside them. For non-water class, segmentation is performed by using module "*i.segment*" with value of threshold equals 0.15. Input of segmentation is group of five bands of RapidEye image inside non-water area. Soil index (SI) is part of VSW index (Yamagata, 1997). SI defines distance between each pixel to soil line in spectral space of Red and NIR band. Segmentation of SI has been extracted using "*r.stats.zonal*" module (Fig. 4a, 4b).

For vegetation class, input of segmentation is combination of vegetation class from pixel-based classification and vegetation extracted from non-water class classification. Input is five bands of RapidEye image, threshold is 0.25. Then segmentation of NDRE, NDRE/S, and DEM results are shown in Fig. 5a, 5b.

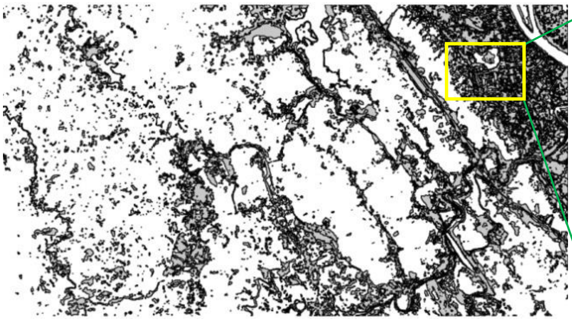

Fig. 4a. Segmentation of class non-water (threshold: 0.15)

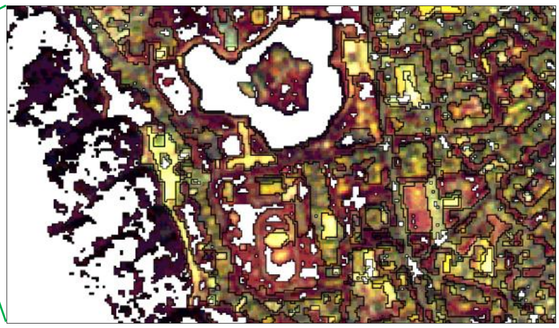

Fig. 4b. Urban area segment of non-water class

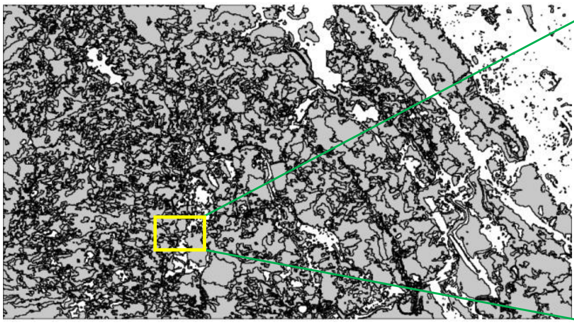

Fig.5a. Segmentation of vegetation class (threshold: 0.25)

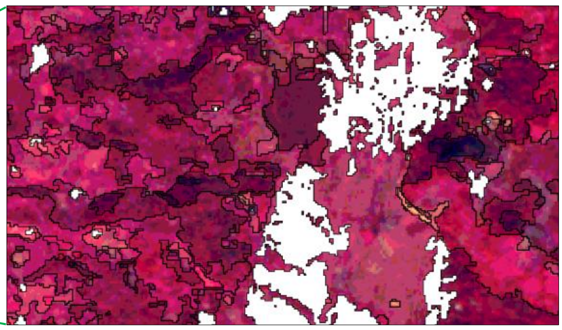

Fig. 5b. A part of vegetation class segment

3.4. Object-based fuzzy system classification

Considering non-water class, there are total four fuzzy sets of input SI: low, moderate, high, very high corresponding outputs: vegetation, agriculture, built-up and soil. For vegetation class, after defining fuzzy sets of two index maps, DEM and the output, "*i.fuzzy.system*" was run to get output of Fuzzy system classification (Fig. 6a, Fig. 7a). After that, reclassification of fuzzy method outputs was done based on membership of each class in order to separate to end classes (Fig. 6b, 7b).

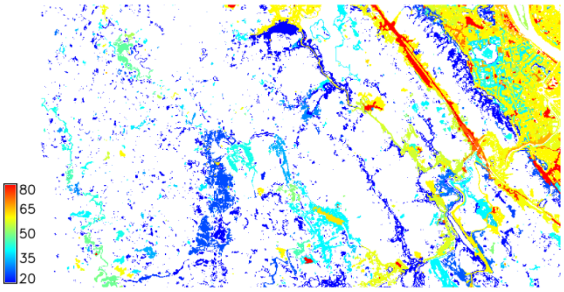

Fig. 6a. Non-water class classification map

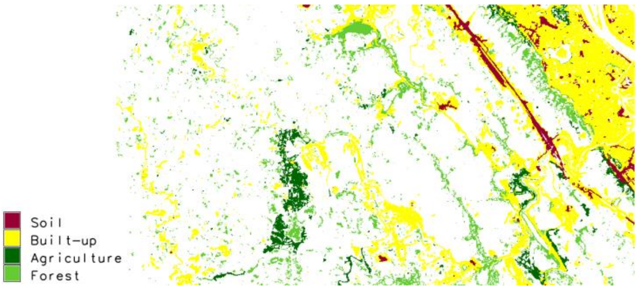

Fig.6b. Reclassified non-water class

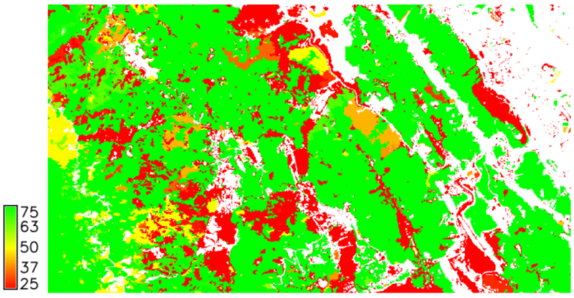

Fig.7a. Forest and agriculture classification map

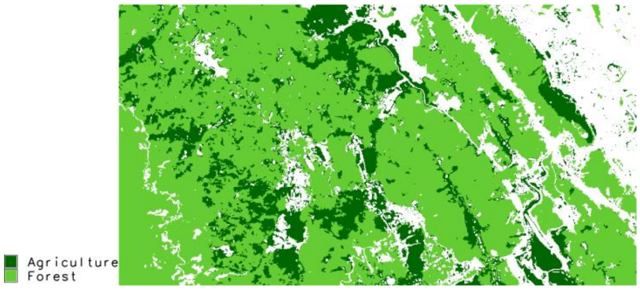

Fig. 7c. Reclassify forest and agriculture classes

4. Result and discussion

Fig. 8 shows classified LULC map of the study area by combining pixel-based and object-based fuzzy classification using spectral indices of RapidEye imagery. Five main classes are separated with the accuracy of 85.7% in total (Table 1).

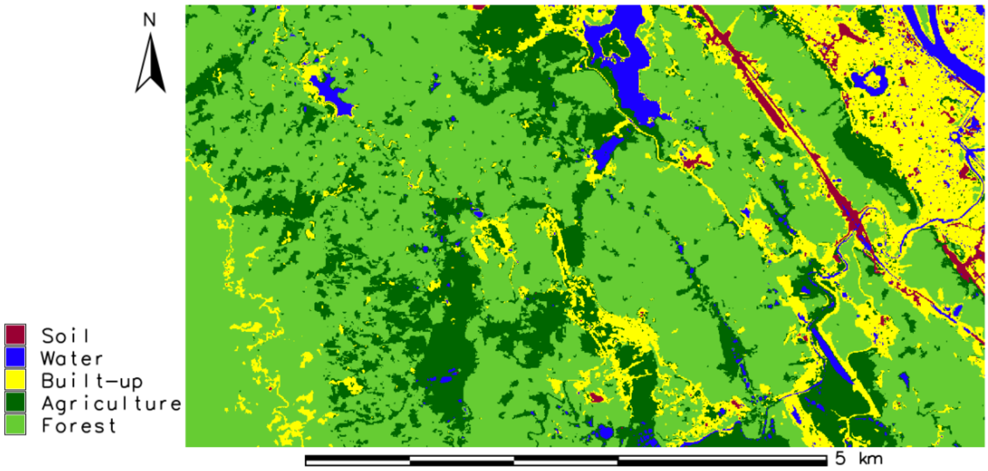

Fig. 8. LULC map of Lao Cai area

The study area is a mountainous area where agriculture includes rice field and paddy fields. Spectral characteristic of many paddy field areas are similar to shrub which belong to forest class leads to lower accuracy of agriculture class where value of producer's and user's accuracy are 73.2% and 64% respectively. Other classes have obtained a higher accuracy, from 75.1% to 98.3%.

5. Conclusion

The research shows that combining pixel-base and object-based LULC fuzzy classification method is able to get high accuracy of the classification results by using spectral indices and FOSS4G. Spectral indices are competent for highlight significant LULC classes, while advancement of FOSS4G is a powerful movement for remotely sensed classification. RapidEye image with Red Edge band high resolution provides useful data for LULC classification purpose. Future, by exploring characteristic of object such as smoothness, compactness (Song, 2004); and combining them with analyzing other spectral indices which show quality and quantity of vegetation can result more detailed LULC mapping.

Table 1.Classification accuracy

Classification \ Reference	Soil	Water	Built-up	Agriculture	Forest	Total	User's Accuracy (%)
Soil	825	0	167	0	0	*992*	*83.2*
Water	0	4290	75	0	0	*4365*	*98.3*
Built-up	131	17	3713	973	112	*4946*	*75.1*
Agriculture	0	58	165	9887	5345	*15455*	*64.0*
Forest	0	11	44	2644	39772	*42471*	*93.6*
Total	*956*	*4376*	*4164*	*13504*	*45229*	*68229*	
Producer's Accuracy (%)	*86.3*	*98.0*	*89.2*	*73.2*	*87.9*		***85.7***

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