IMAGE-BASED VERSATILE LU INFORMATION: A MULTIDIMENSIONAL CLASSIFICATION SCHEME TO SUPPORT LOCAL PLANNING IN INDONESIA

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KEYWORDS: Remote sensing, Land-cover, Land-use, Mapping, Classification, Planning, Decision support, High resolution

ABSTRACT

Land-cover (LC) and Land-use (LU) are recognised as important factors in environmental assessment and planning. However, different applications normally require different LC/LU information contents. Various planning tasks might face difficulties when two or more LC/LU maps with different classification schemes share the same area of interest. Consequently, redundant works on LC/LU surveys of the area are carried out in order to make sure that the collected LC/LU maps to be used contain relevant information. In order to overcome such problem, a versatile LU information system (VLUIS) is developed. The VLUIS is mainly developed based on remotely sensed imagery. Its versatility is characterised by the following aspects: (a) multilevel categorisation with respect to particular range of spatial resolution; (b)multiple attributes of LC and LU contained in a classification scheme, represented by five LU dimensions, *i.e.* spectral, spatial, temporal, ecological, and socio-economic function; (c)layer stack data storing model for those dimensions enabling flexible attribute retrieval through a spatial query for relevant applications. In this paper, examples of extraction methods using remotely sensed imagery, *i.e.* Landsat TM/ETM⁺ (30 m) and Quickbird (2.4 m) are given, particularly for the first dimension of the VLUIS. Semarang area in Central Java, Indonesia, was chosen due to its relatively complex LU phenomena within a narrow strip of image coverage. The use of the VLUIS is put in the context of refinement of the KDLD (Key Dataset for Local Development), which has been developed by various local governments in Indonesia. As compared to Landsat TM/ETM+-based image processing, the use of high-spatial resolution imagery such as Quickbird multispectral requires more complex spatial analysis in order to derive versatile LU dataset.

1. INTRODUCTION

Land-cover (LC) and Land-use (LU) are recognised as important factors in environmental assessment and planning. Unfortunately, such information is still difficult to obtain when quality, relevance, and newness are considered as major criteria. Fresco (1994) claimed that accurate data on LU and LU changes are not easily found, both in the global and continental scales as well as the national and regional ones. In order to support planning, remotely sensed imagery has been used as a major source of LC (LC) and LU (LU) information worldwide (Stefanov *et al.*, 1999; Campbell, 2002; Tapiador and Casanova, 2003). Regional and urban planning activities in many countries also make use of LU information, which is frequently derived from remotely sensed data (Carlson and Sanchez-Azofeifa, 1999).

Various techniques in remote sensing can derive LC and LU information with a great diversity in contents. This diversity is also related to the fact that LC and LU are different concepts. The differences had been discussed by various authors, *e.g.* van Gils *et al.* (1990). However, most classification schemes intentionally exchange both concepts (*e.g.* Anderson *et al.*, 1976; Malingreau and Christiani, 1982; Sandy, 1982). In addition, it should also be realised that LU is a multidimensional concept, which may be viewed from various perspectives ranging from spectral (related to LC), spatial, temporal, ecological, socio-economic function and legal aspects. Visual interpretation could directly derive both LC and LU information at particular levels or scales, but digital image processing that is not supported by GIS analyses can generally derive LC classes only. Thus, under this circumstance, LC and

LU maps of the same area that were produced with different approaches may represent different information, which may lead to users' confusion in planning.

Problems and situation described in the aforementioned paragraphs exist in Indonesian planning program, particularly at both provincial and local levels. The local planning, according to Suroso (2000) is mainly characterised by "more LU oriented" programs such as LU zoning and allocations, conservation and measures parallel with coordination and implementation of policies. On the other hand, during the past fifteen years, many provincial and local authorities have developed a so-called Key Dataset for Local Development (KDLD) containing a set of maps for supporting a range of planning activities. It was found that the quality of maps stored in the KDLDs is not adequate to support planning tasks due to their newness, accuracy, and relevance. Among others, LC/LU maps are recognised as important information with the lowest reliability due to their low quality. As a consequence, each institution tends to develop its own LC/LU information with limited consultation to the others. Therefore, redundant works on LC/LU surveys take place and incompatibilities between maps partly covering the same areas come up.

Based on this current situation, problem associated with the local planning in Indonesia can be viewed from the LU information perspective, *i.e.* there is a need for developing up to date, accurate and relevant information on LC/LU to support local planning tasks in Indonesia. To solve such a problem, efforts should be carried out in conjunction with the advances in remote sensing technology, which can deliver various spatial thematic data required by various local planning tasks.

2. STUDY OBJECTIVE

The objective of this study was to develop an image-based multidimensional LU classification scheme as a part of the development of versatile LU information system (VLUIS) for local planning in Indonesia. Following the classification scheme development, example of LC information extraction as the first dimension of the VLUIS was given. Image datasets of Landsat ETM+ and Quickbird covering Semarang area, Central Java, Indonesia were used. This study is a part of a longer term research aims to develop versatile LU classification scheme and information extraction methods for each category within the scheme, followed by a demonstration in applying the obtained spatial data to support several local planning tasks.

3. PREVIOUS WORKS

Studies on the development of LC/LU classification systems have been carried out by various authors. One of the most eminent systems is the USGS LC/LU classification system (Anderson *et al.*, 1976), which mixes up LC and LU terms in its categorisation. The USGS LC/LU classification system is widely used in various projects in the USA. For Indonesian environment, Malingreau and Christiani (1982) and Sandy (1982) also developed systems mixing up LC and CU concepts. Van Gils *et al.* (1991) proposed a two-level 'ITC World LC and LU Classification', which tried to separate LC from LU categories and simultaneously established relations between the two. Recent development of LC/LU classification systems were undertaken by Food and Agricultural Organisation (Jansen and Di Gregorio, 1998), Young (1998) and Cihlar and Jansen (2003).

Similarity between all aforementioned classification systems is the use of single attribute for each category on each level. The single attribute of LC/LU categories may become problematic at the subtler level, *e.g.* level III and IV of the USGS classification system, since more detailed information in a single attribute tends to be more specific. Thus, at a subtler level, translation or conversion from a classification scheme to another is inhibited. As a consequence, it is more difficult to use similar categories under different schemes for practical purposes, *e.g.* monitoring of LU change. That is why Young (1998) emphasised the need for development of LU classification system containing multiple attributes comparable to soil properties found in the World Reference base for Soil Resources.

By using digital satellite imagery, multispectral classification can automatically derive LC-related spectral classes (Jensen, 1996; Mather, 1999). The tentative categories can then be regrouped and relabelled into more meaningful LC classes. Liu *et al.* (2002) suggested the combination of various automatic image classification methods, *i.e.* maximum likelihood, expert system, and artificial neural network for improving land cover map accuracy. Derivation of subtler information on LC or LU through per-pixel image classification can also be done with contextual information (Stuckens *et al.*, 2003), such as landscape characteristics related to soil properties and slope steepness (Folly, 1996; Danoedoro, 2001; Ehlers *et al.*, 2003).

4. METHODS

4.1. Development of Classification Scheme

The classification scheme development was started with the distribution of questionnaires to 36 stakeholders related to planning in the study area. Findings obtained from the questionnaire data was analysed together with previous works dealing with LU based environmental assessment and modeling. In addition, several classification schemes widely used such as USGS LC/LU classification systems (Anderson et al., 1976), LC/LU classification system for Indonesia (Malingreau and Christiani, 1982), ITC (van Gils et al., 1991) were taken into account. Moreover, various concepts related to LC, LU as viewed from spectral, spatial, temporal, ecological, and socio-economic aspects were also considered. These include spectral characteristics of various objects (Hoffer, 1978; Curran, 1985; and Jensen, 1996); spatial pattern and geographic position/ site (Lillesand and Kiefer, 2000); temporal pattern of LC and LU (van Gils et al., 1990), tropical ecology (Ewussie, 1990; Osborne, 2000); and socio-economic aspect of LC and LU (Sutanto, 1986; Jensen, 2000).

 Table 2. Description of each LU dimension used in this study

LU DIMENSION	DESCRIPTION
Spectral	Strongly related to, or may directly be identified based on, spectral information of the objects. In general, the spectral dimension is expressed by cover types
Spatial	Related to particular spatial pattern or arrangement, position or site, which is normally used as an additional key factor (besides spectral dimension) to distinguish one feature from others, e.g. river, lake, regularly spaced stands, interleave planting, coastal mudflat
Temporal	Related to temporal or seasonal changes, e.g length of indundation and crop rotation. Information related to spectral and spatial aspects is also required to determine temporal dimension.
Ecological	LC and LU forms express interaction between vegetation, animals and human activities with the land they exist. Their existence also represent the environmental characteristics of the area, <i>e.g.</i> mangrove formation, upland agriculture, slum areas
Socio-economic function	Basically, many LC types and LU functions have economic or socio-economic functions too. However, the socio-economic dimension needs to be explicitly presented, if they have.
Legal	Basically it is difficult to extract using remotely sensed imagery.

A multilevel classification was considered more suitable for local regions in Indonesia, which show a wide range of areal coverage. Therefore, various satellite imagery with various spatial resolutions were taken into consideration. Previous works using various satellite data were reviewed with respect to the level of details of the categories generated, methods of processing used or developed, and accuracy levels reached. The works of Phinn *et al.* (2000) and Phinn *et al.* (2002) were also taken into account. Meanwhile, types of information to be included in LU categories were also specified with respect to the previous works in environmental applications.

4.2. Image Analysis and Classification

Image classification was run based on the classification scheme. In this study, the first (spectral) dimension of the versatile LU information was derived using image processing software. As the study is still in progress, the other dimensions are being explored using integration of visual interpretation, image processing, and GIS.

4.2.1. Data and softwares

Two image dataset were used in this study, i.e. Landsat Enhanced Thematic Mapper Plus (ETM+) bands 1-5 and 7, and Quickbird high spatial resolution imagery with multispectral bands 1-4 and panchromatic. The ETM+ imagery (path/row 120/065) was recorded on 21 August 2002, while the Quickbird imagery was recorded on 31 August 2002. The whole area covered by the Quickbird is also covered by the Landsat. In this study, two image processing softwares were used, i.e. ENVI 4.0 for most processing tasks, and ERDAS Imagine 8.7 for particular ones. The ENVI software was mainly used for making image subset, selecting samples through regions of interest (ROIs), assessment of samples' statistics, execution of multispectral classification and assessment of classification accuracy. The ERDAS Imagine 8.7 was mainly used for multiresolution image merging, image reprojection and resampling, and recoding of pixel values related to LC labels.

4.2.2. Analysis

During the first stage, each image dataset was treated differently. After geometric correction and subset cropping, the Landsat ETM+ data was prepared for multispectral classification at 30 m pixel size. Meanwhile, a multi-resolution merging of Quickbird imagery using Brovey transform (Vrabel, 1996) was carried out in order to create a new colour composite imagery with higher spatial resolution, *i.e.* 0.60 m. Meanwhile, The original Quickbird multispectral image dataset (2.4 m spatial resolution) was also preserved for multispectral classification.

Image classification was performed in three stages. Firstly, ROI-based sampling that was performed interactively. Selection of ROIs was mainly based on the collected field data, even though some additional ROIs were chosen based on local knowledge, topographic map as well as available aerial photographs. ROI names were given with respect to the prepared classification scheme with a slight modification, e.g. shallow water1, shallow water2, high density broadleaves on shaded areas. Every time a ROI is chosen, the sample statistics were evaluated and the class separability between existing ROIs was also calculated. Especially for Quickbird image dataset, the ROIs selection was also guided by the display of Broveytransformed multiresolution imagery. By doing so, homogeneity within each ROI could be evaluated directly, both visually and statistically. Secondly, image classification and refinement using class merging. Image classification was performed using maximum likelihood algorithm. Prior to the classification execution, computation of statistical separability between classes was done using transformed divergence and Jeffrey-Matushita indices (Jensen, 1996). Thirdly, post-classification using selective majority filtering was applied in order to aggregate pixels of patchy classes into most common label within a given window, and to simultaneously preserve particular classes that are considered minority within a given window (*e.g.* linear features with 1-2 pixels width). By this selective majority, a pixel-based generalisation can be applied without losing important information conveyed by particular individual pixels.

5. RESULTS AND DISCUSSION

5.1. The Multidimensional Classification Scheme

Figure 1 shows how particular categories under each dimension are broken down into subtler classes. Based on the developed categorisation, examples of spectral-related cover types classification using Landsat ETM+ and Quickbird imagery are given.

5.2. Example for the First Dimension: Automatic Classification

Since the large number of classes obtained from the spectral classification contains similar generic LC categories, a class merging operation needs to be run. During this stage, 40 spectral-related tentative cover classes from Landsat ETM+ image was merged to 27 LC classes with respect to the specified categories and spatial resolution under spectral dimension of the versatile LU classification scheme. By using the same procedure, 85 tentative classes obtained from multispectral classification were merged to 48 spectral dimension LC classes according to the versatile LU classification scheme. Figure 8 shows the result.

Accuracy assessment of the classified Landsat ETM+ and Quickbird images showed that the level of accuracy increases when the post-classification processes applied (Table 2). The immediate result of multispectral classification, *i.e.* original classified image was less accurate as compared to the classified images followed by class merging. Class merging consequently reduces the number of pixels of omission and commission. This particularly gives positive effect for tentative classes having relatively similar characteristics, *e.g.* shallow water_1 and shallow water_2, which were then be merged into shallow water.

Table 2.	Accuracy leve	l of the classified	images:	original,	merged, a	and majority-	filtered classes.
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Image data and	Accuracy levels of classified data with respect to Versatile LU Classification Scheme							
number of bands Original classified image		Merged classes		Global majority filtering	Selective majority filtering			
	Nr.of	Accuracy	Nr.of	Accuracy	Accuracy	Accuracy		
	classes	Overall & Kappa*	classes	Overall & Kappa*	Overall & Kappa*	Overall & Kappa*		
Landsat-7 ETM+	40	86.84 %	27	92.56 %	94.38%	94.13%		
(6 bands)		(0.8628)		(0.9211)	(0.9434)	(0.9378)		
Quickbird	85	68.75 %	48	79.02 %	87.05%	85.90%		
(4 bands)		(0.6813)		(0.7829)	(0.8656)	(0.8539)		

* The Kappa coefficients are put within brackets

SPECTRAL-RELATED COVER DIMENSION 1 Water bodies ▶11 Asphalt ▶4121 Concrete, non-coloured Asphalt, concrete 2 Vegetation cover 412 Concrete and cemented surfaces 3 Barren land/open soils ➡13 Fibre cement ▲4122 Concrete, coloured (as roof tiles) ➡42 Compacted clay surfaces 4 Paved / impervious Metal, glass, fibreglass and plastic surfaces surfaces ____44 Others SPATIAL DIMENSION 1 Water bodies 11 Sea ▶ 12 Lake ▶131. River 2 Vegetation structure and composition 3 Barren land and open ► 13 River and channel ► 1321 Irrigation channel soils 14 Pond ►132. Rivulet and channel ► 1322 Drainage channel 4 Built-up/Paved ► 15 Others 1323 Irrigation and surfaces drainage **TEMPORAL DIMENSION** 1 Length of inundation-▶ 21 Relatively stable/no related features change Vegetation change->22 Seasonal change in ►241 Continuous planting ► 2421 Cropping period related features vegetation cover 3 Open soil change-►23 Growing vegetation ► 242 Interrupted planting related features 4 Development stage-▶24 Rotation planting ▶ 2422 Fallow period related features **ECOLOGICAL DIMENSION** 1 Aquatic environment 21 Freshwater wetland ►221 Non-vegetated ►2221 Avicennia zone tidal mudflat 2 Wetland and riverside ► 22 Coastal and estuarine ► 2222 *Rhizopora* zone environment environment 222 Mangrove formation 3 Lowland and alluvial 23 Riparian vegetation ▶ 2223 Bruguiera zone land environment 4 Montane and steeper 2224 Others lands environment 5 Built environment DIMENSION OF SOCIO-ECONOMIC FUNCTION ► 341 Continuous ricefields 1 Water-based utilisation ▶ 31 Pasture land 2 Forest-based utilisation ➡ 32 Tree-crop planting ► 342 2x rice + cashcrops ► 3431 1x rice + single cashcrop 3 Agricultural uses ► 33 Non-woody plantation →343 1x rice + cashcrop-4 Settlement and 34 Inundated ricefields ▶ 344 2x rice + vegetables 3432 1x rice + multiple infrastructures cashcrops 35 Dryland cultivation ➡ 345 1x rice + vegetables ► 36 Agroforestry system ➡ 346 Rice + fish rearing LEVEL 1 LEVEL 2 LEVEL 4 LEVEL 3 (>100 m spatial resolution) (30-100 m spatial resolution) (5 – 30 m spatial resolution (<5 m spatial resolution)

Figure 1. Examples of categorisation developed for each land-use dimension.

Statistically, however, global majority filtering gives a slightly better accuracy level than the selective one. The selection of field reference data and its digitisation in terms of ROIs have created solid areas with homogeneous labels, matching the result of global majority filtering that can successfully remove minor variation within a given window. On the other hand, the use of selective majority filter preserving particular classes with 1-2 pixels width has generated slightly heterogeneous features surrounding them. As a result, the omission and commission slightly increased and the overall accuracy a little bit decreased as compared to the global majority filtered LC map.

Despite the higher overall accuracy levels and Kappa coefficients for global majority filtering result of both Landsat-7 ETM+ and Quickbird images, the selective majority filtering gives more reasonable result, particularly in preserving road and small river network, as well as clusters of settlement with clay roof tiles. The global majority filter tends to generalise these features so that they might be omitted from the scene.

The classification result also shows that Quickbird image with 2.4 m spatial resolution tend to give lower classification accuracy as compared to those with coarser spatial resolution such as Landsat-7 ETM+. It is parallel to the statement of Aplin *et al.* (1999) who said that an increase in spatial resolution is associated with an increase in internal variability within land parcels ('noise' in the image), which may finally decrease the classification accuracy on a per-pixel basis. Moreover, the Quickbird image with 11-bit level of radiometric resolution (0-2048 grey level for each band) can show different spectral pattern for the same objects found in Landsat-7 ETM+ image, which is processed in 8-bit radiometric resolution.

Several works on high-spatial resolution imagery have proven that per-field classification (*e.g.* Aplin *et al.*, 1999) and textural or neighbourhood analyses within a given window (*e.g.* Jenkins and Phinn, 2002) might generate more accurate classification results than the 'traditional' per-pixel classification. Therefore, it is necessary to explore such methods for improving the classification result in the next phase of this study. However, this study also demonstrated that relatively subtler categorisation of cover types under the versatile LU classification scheme can be achieved through a careful sampling, classification and post-classification processes.

5.4. The Future Works

Once the versatile classification scheme is established, it requires further studies concentrating on the development of image analyses and classification methods for generating categories under other dimensions. Although it is obvious that all categories specified within the classification scheme can be mapped using visual interpretation with adequate support of field data, automated mapping methods are still needed for more detailed and consistent information extraction. The availability of high-spatial resolution imagery such as Ikonos, Quickbird and Orbview should be in balance with the development of image analysis and information extraction methods.

To address this challenge, there are two sub-topics of research for the future works should be conducted:

- a. Development of image classification and information extraction methods with respect to each category specified in the versatile LU classification scheme;
- b. Demonstration of versatility of the developed VLUIS in various local planning tasks.

Research in the image classification and information extraction methods will be carried out in the next phase of the study. During this phase, methods and their mapping accuracies will be assessed in order to find the most appropriate and efficient image processing techniques for generating versatile LU information. In order to demonstrate the VLUIS versatility, several local planning tasks that require LU information will be chosen for modelling. The tasks include industrial site selection, monitoring LU change, and soil loss prediction models.

6. CONCLUDING REMARKS

During the past years, data availability and quality have become one of main interests in the development of GIS. Following these needs, various users also require model applicability and development. The development of VLUIS can be put in this context, by which the LU data are supplied and stored in such a way so that various models and applications may use it as a common reference for solving their own problems. From the local planning perspective, the availability of VLUIS should be put within the frame of KDLD re-establishment, in which the improvement of LU information should also be undertaken together with other spatial data. Therefore, the applicability of the KDLD to support local planning tasks can be realised with the support of both LU and other relevant spatial data.

Landsat systems have been serving to provide data continuously during the past 30 years, and the data can be used as a good basis for monitoring system at both regional and local levels. This study has proven that the Landsat-7 ETM+ imagery is also accurate to be used as a basis for the VLUIS' first-dimension (LC type) mapping. However, further studies are required in order to ensure that this kind of imagery is also accurate for generating other VLUIS' dimensions.

It was also found that the Quickbird imagery, with its 2.4 meters spatial resolution, is accurate enough for satisfying LU mapping tasks with respect to the VLUIS' first dimension classification scheme. Although 85% accuracy level might be considered as 'marginally accurate' according to the minimum level of LU classification accuracy (Campbell, 1983), more complex analyses can still be developed in order to increase its accuracy, and these will be conducted in the Phase II. It should also be noted that the processing methods applied to both Landsat-7 ETM+ and Quickbird imagery were standard algorithms followed by a simple neighbourhood analysis techniques, which could be done using most image processing systems available in the marketplace. Thus, the future works may also be expected to explore other methods for increasing the accuracy levels of the classification.

ACKNOWLEDGEMENTS

The authors wish to thank the Amsterdam Trust Fund, who has made the poster presentation of this paper possible by supporting additional funding. Image data delivery from LAPAN Indonesia (Landsat ETM+) and Sinclair Knight Mertz Australia (Quickbird) are also acknowledged.

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