MULTISOURCE CLASSIFICATION FOR LAND-USE MAPPING BASED ON SPECTRAL, TEXTURAL, AND TERRAIN INFORMATION USING LANDSAT THEMATIC MAPPER IMAGERY

A Case Study of Semarang-Ungaran Area, Central Java

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ABSTRACT

Automatic classification of remotely sensed digital data is recognised as a robust and efficient method for mapping various land-cover types over a large area. However, when more abstract concept such as land-use is required, the automatic classification methods cannot be fully useful. This is due to the fact that land-use is related to various landscape factors, and cannot be mapped merely based on its spectral reflectance. This study tried to develop a knowledge-based technique that incorporates textural and terrain information of the image scene into a spectral-based decision making process for land-use labelling. To do so, six reflective bands of Landsat Thematic Mapper (TM) covering Semarang-Ungaran area, Central Java, were used. In addition, all bands were then be filtered using the so-called textural filter, which can accentuate several statistical parameters within a given window. A variance parameter was chosen in order to extract heterogeneity within every 7x7 pixels, and the variance values of the whole image dataset were then stored as a set of texture-filtered bands. Three bands with the lowest 'between-band correlations' were chosen and added to the reflective bands. Based on the nine-layer image dataset, a standard multispectral classification using maximum likelihood algorithm was run. Parallel to this process, a visual interpretation using heads-up digitisation was carried out in order to generate a terrain unit map containing land characteristics relevant to spatial distribution of the land-use in the study area. Finally, the terrain unit map was superimposed with the tentative land-cover map derived from the multispectral classification process. A final land-use map was generated from the multisource data integration, controlled by a formalised knowledge about ecological relationship between land-cover, land-use, and land characteristics exist in the field. It was found that the overall accuracy level of the final land-use map is higher as compared to the result generated from six-band classification. However, the use of textural filter also created an 'edge-effect', which shows misclassified pixels alongside the borders of particular land-use categories. The edge-effect also leads to lower accuracy levels for the corresponding land-use categories. In addition, based on the research findings, further research agenda was also set up.

Keywords: ***textural information, multisource classification, knowledge-based technique, land-use mapping***

INTRODUCTION

Background

Land-use information is very important in nearly all applications dealing with the study of landscape. Due to its significant role, many applications strongly require accurate, up to date and relevant land-use information. During the last 30 years satellite remote sensing technology has been serving to provide this kind of information, in conjunction with the conventional aerial photographs (Lillesand and Kiefer, 2000).

Even though satellite images have been enhanced in terms of spatial, spectral, and radiometric resolutions, the need for improved methods in automatic land-use information extraction is still pertinent today. Recently, various remote sensing systems in terms of platforms, sensors, ways of recording, and wavelength regions have been operated (GeoImage, 2002; Phinn, 2002). With respect to this current situation, Plummer *et al.* (1996) emphasised the importance of making parallel advances in the science of interpreting and applying the data to solve environmental problems.

As compared to more established visual interpretation, however, the automatic image information extraction is still lacking of spatial context consideration, since the complex thinking process of human brains blend the spectral, spatial, ecological, and intuitive aspects in their 'experience'. Lillesand and Kiefer (2000) described eight elements of interpretation; and until recently, most of them cannot be extracted automatically from any digital image.

In order to approach this complicated process, many methods of automatic information extraction have been developed. Some of them are concentrated on more sophisticated analyses of spectral information, and some others try to integrate spectral, spatial, temporal and ecological aspects in geographic information systems (GIS) environment. Examples of these methods are hyperspectral analyses (Curran and Kupiec, 1996; Datt *et al*, 2002), fuzzy methods (Jensen, 1996), artificial neural network systems (Baret, 1996; Campbell, 2002), multisource approaches within GIS environment (Richards, 1993, Danoedoro, 1993; Folly, *et al.*, 1996, Danoedoro, 2001), sub-pixel analyses (Phinn *et al*, 2001), and spatial context consideration using neighbourhood and textural information of adjacent pixels (Jenkins and Phinn, 2002).

As viewed from remote sensing perspective, Java Island in Indonesia represents a region with high complexity, both in agricultural and urban land-use phenomena. Water availability for supporting agricultural activities varies with respect to the genetic-dependent terrain characteristics. High pressure on land caused by a huge number of population leads to the intensive land-use on small-sized fields. In addition, urban phenomena do not show a well-structured zonation or stratification in terms of industrial, commercial and residential features, which is mostly found in more developed countries. Instead, they tend to mix up together. The same case is found in the so-called rural settlement areas, where the semi natural vegetation, crops and buildings exist in clusters (Danoedoro, 1993). On the other hand, in a typical wet tropical land-use like in Java, there is a very close relationship between terrain characteristics and the land-use (Danoedoro, 2001). This relationship clearly appears in the rural areas; where technology limitations and terrain characteristics make some land-use types exist in particular terrain units only. All these things make standard automatic classification of remotely sensed imagery does not work to generate land-use maps.

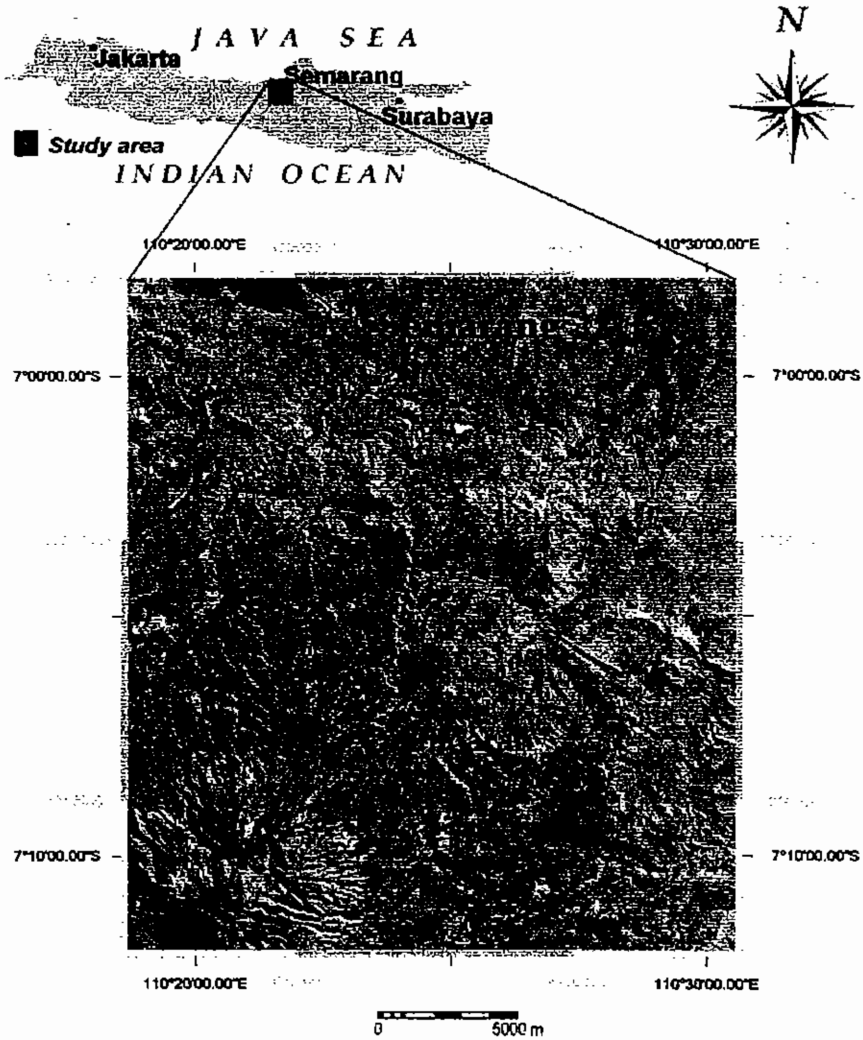

Figure 1. Landsat Thematic Mapper imagery recorded on 25 June 1996 showing the study area. The false colour image composition is TM4 (red), TM5 (green) and TM1 (blue).

Problem Statement and Significance

Based on the aforesaid background, it can be concluded that a standard procedure formalised in image processing menus is not adequate to derive land-use information of such areas. There is a need to combine various functionalities, which can accentuate and derive information relevant to land-use, and finally they can be integrated to provide the final land-use map.

With respect to the aforesaid problem, development of image processing method for generating accurate land-use information, particularly for areas like Java, is a necessity. Accurate land-use information is very important for various applications and environmental models, since its inaccuracy contributes a significant role to error propagation in the models. The method used in this study was expected to provide more accurate land-use information, which may contribute to better environmental planning and modelling results.

RESEARCH OBJECTIVE AND EXPECTED RESULTS

Research Objective

The objective of this study was to develop a methodology for integrating spectral, textural, and ecological aspects in classifying Landsat Thematic Mapper image to derive a land-use map.

Expected Results

The expected results of this study: (1) model in integrating spectral, textural and ecological information for land-use mapping based on satellite image, and (2) land-use map of the typical densely-populated wet tropical region, accompanied with an accuracy assessment.

LITERATURE REVIEW

Understanding of land-use from the remotely-sensed imagery is underlain by a thorough knowledge about land-cover types and their spectral characteristics within several ranges of wavelength. Visual interpretation based on first- and second-generation satellite images had been discussed by Campbell (1983) and van Gils *et al.* (1990). As a basis for digital interpretation, Hoffer (1978) and Jensen (2000) discussed the spectral characteristics of typical single objects such as water, soil and vegetation across visible and reflective infrared regions (0.4 – 2.3 μm). Each object was discussed with respect to its state or condition, which gives influence on the recorded reflectance. Leaf maturity, pigmentation (such as chlorophyll and anthocyanin), and water or moisture content have strong influence. For soils, the content of silicate substance, iron oxide and soil wetness were also taken into account. Finally, water turbidity also plays important role, particularly in the visible region.

Although latest studies using imaging spectrometry found that much more biophysical, including chemical, characteristics of the objects can be studied (Curran and Kupiec, 1996), Hoffer's explanation is still adequate for conventional image classification using relatively broad bands images like Landsat TM/ETM+, SPOT or IKONOS. Hoffer's explanation, however, is merely based on the individual objects, which is less appropriate to be applied in real situation where vegetation (not only leaves), soils and water are mixed together in the complex feature of landscape. Explanation of the reflectance of soil, vegetation, water, and their mixture could be found in the work of Richardson and Wiegand (1977). They proposed the so-called vegetation and soil lines in the spectral space, particularly in red versus near-infrared spectral space. During the last 20 years, the soil and vegetation lines are still utilised to develop various vegetation indices.

One of the most common functions within any image processing system is image classification. This function is very important for land-use information extraction. An automatic image classification is normally run using multispectral data. The basic assumption of this method is that objects can be recognised merely based on their spectral characteristics (Jensen, 1996). In addition, Phinn (2002) stated that there are major assumptions conceptually used in image classification, *i.e.* (a) a high resolution application, in which each pixel is made up entirely of one surface cover type (pure pixel), (b) the pixels making up one surface cover type are assumed to have similar spectral signatures, (c) different surface cover types have significantly different spectral signatures.

In an automatic classification, statistical information of the sampled pixels is important for the classification decision-making process. Another key input is the algorithm used for developing 'decision boundaries' between samples. Richards (1993), Jensen (1996) and Lillesand and Kiefer (2000), for examples, discussed the non-parametric (*i.e.* box or parallel-epiped) and parametric (*i.e.* minimum distance to mean and maximum likelihood) approaches to the classification procedures.

Since all aforementioned algorithms in multispectral classification are underlain by the same basic assumption, they cannot differentiate pixels of different objects with similar spectral signatures. Furthermore, different land-use categories may be composed by similar cover types with different spatial configurations. A spatial context consideration is needed in this case. Danoedoro (1993) and Danoedoro (2001), for example, introduced terrain unit and digital elevation maps to improve Landsat TM image classification result. Jenkins and Phinn (2002) developed a spatial reclassification approach to a very high resolution satellite image (IKONOS) covering an urban area. Such approaches take into account the proportion of cover within a known land-use unit, and use the relationship between land-cover proportion and land-use type to derive a land-use map.

Spatial consideration in terms of feature roughness or texture is also important to differentiate various land-use types. Lillesand and Kiefer (2000) discussed the use of this texture approach, by applying a moving window or kernel in order to separate *smooth* (homogeneous or low frequency) features from the *rough* (heterogeneous or high frequency) ones. Anys *et al.* (1994) and ERDAS Field Guide (1999) discussed the use of statistical parameters to express various textural information using filter such as skewness, standard deviation and variance. Furthermore, a neighbourhood analysis, which considers the existence of pixels representing particular types of cover within a moving window (ILWIS 3.1 Manual, 2002), can be applied to recognise the composition of land-cover types for particular land-uses.

Accuracy assessment of classified image can be carried out by comparing the image with a standard or reference information. Short (1982) and Congalton (1991) discussed the use of error matrix with commission and omission in order to assess the accuracy of each class and the overall result. In digital format, this approach may be done by overlaying the 'standard' map with the newly classified image (ILWIS 3.1 Manual, 2002) or by comparing a set of randomly chosen pixels of classified image with corresponding pixels of the reference map (ERDAS Field Guide, 1999).

DATA AND METHODS

This study made use of Landsat TM image (all six reflective bands, range from blue to middle infrared) as the main source of data. This image dataset is accompanied by several supporting information, including topographic map and an existing land-use map of the area. Geometric pre-processing was carried out in order to set the image and the ancillary spatial data into the same geographic reference system. Subsequently, image filtering process was run in order to generate texture-filtered bands. A multispectral classification procedure followed, in which all reflective bands of Landsat TM image were put together with selected texture bands in a layers stack. This procedure was run to generate a tentative land-cover map of the study area.

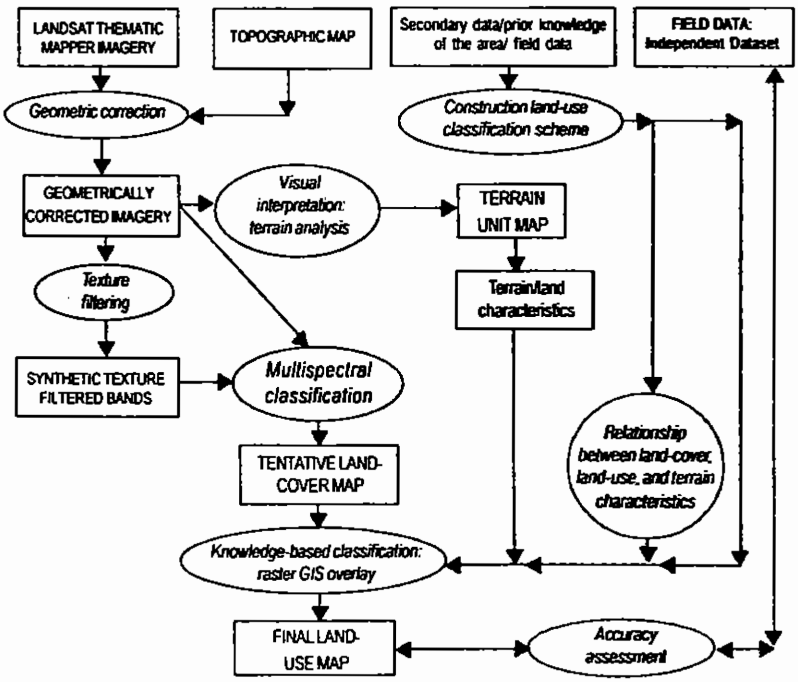

Figure 2. Methods used in this study

Parallel to the automatic classification of tentative land-cover, a visual interpretation was carried out in order to derive terrain units related to land-use categorisation in the study area. To do so, an on-screen digitisation was performed on geometrically corrected image so that a terrain map in a digital format can directly be generated. Finally, the tentative land-cover classes were integrated with the terrain unit data in a raster GIS environment. The process was controlled by the knowledge about their relationships. An accuracy assessment of the classified image was then undertaken, in order to make sure that the developed method is adequate to be considered as an alternative for land-use mapping (Figure 2).

Data and Softwares

This study made use of the following spatial datasets: (1) Landsat TM covering the area of Semarang, Central Java, with 30 meter spatial resolution, 6 bands (TM1 – TM 5 and TM7), acquired on 25 June 1996, corrected at level 6 in LAPAN ground station. The digital image was then resampled to 25 m pixel size; (2) AMS topographic map 1964, at scale of 1:50,000, comprising sheets of Semarang North, Semarang South (Ungaran), and Ambarawa.

The softwares used in this study were ERDAS Imagine 8.5, ENVI 3.5, and ILWIS 3.1 raster-based GIS. ENVI 3.5 was mainly used for creation of image subset, geometric correction and mosaic creation of scanned topographic maps. ERDAS Imagine 8.5 was mainly used for spatial enhancement in terms of texture filtering, supervised multispectral classification and statistical evaluation of the pixel samples. ILWIS 3.1 was used for geometric correction of the Landsat image dataset, visual interpretation of terrain/landform using on-screen digitisation, vector-to-raster conversion, raster maps overlay for final land-use map generation, and cartographic presentation of the results.

Methods

Data Preparation

Data preparation comprised creation of image subset, bands selection and geometric correction. Since the image has been corrected radiometrically at level 6, and this would not be used in conjunction with other image dataset for spectral analysis purposes, a further radiometric correction or calibration was not performed. Creation of image subset was carried out with respect to the extent of the study area, as well as the selection of bands to be involved in the multispectral classification. Correlation between bands was evaluated in order to choose the most representative spectral bands for the classification purpose. However, the TM6 emissive band was excluded in the first step due to its difference in terms of spectral domain and spatial resolution (120 m), as compared to the other reflective bands.

Texture transformation

Texture transformation in terms of filter/moving windows was applied in order to derive textural information related to the homogeneity of adjacent pixels within the image. This transformation was expected to provide differentiation between areas with different frequency, *e.g.* urban, forest, and densely populated agricultural areas. A 7x7 kernel was used instead of 3x3 or 5x5, since the smaller kernels tend to accentuate edges with a big contrast, *e.g.* pixels alongside the rivers and coastal lines.

Supervised classification

A supervised classification was applied to the image dataset, supported by prior knowledge about the area and field observation. During the sampling stage, the display of colour composite image was set to various combinations in order to obtain maximum clarity of the features. The labelling process of samples did not directly refer to the existing classes/categories in the land-use map. Two things were taken into account here, *i.e.* (a) a 'new', purposively built, classification scheme will be used instead of the existing one; (b) the spectral characteristics recorded as pixel values do not directly reflect the "the use" of the land. Instead, they reflect the basic form of the land-cover.

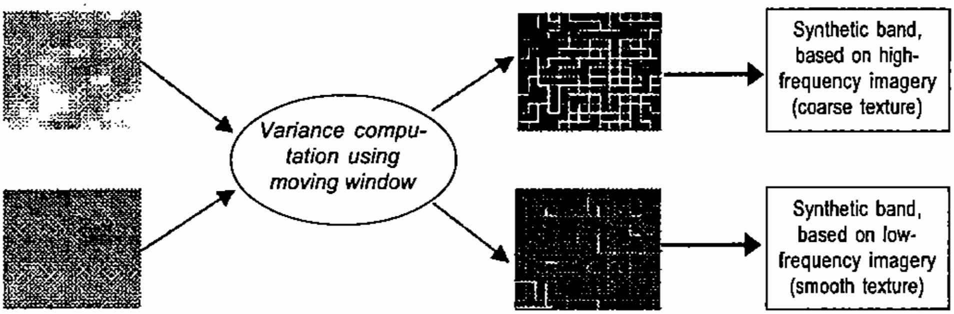

Figure 3. Texture filtering based on variance within given window to extract information about heterogeneity of the neighbouring pixels

The sampling process was also guided by the evaluation of the feature spaces. Relative position of the sampled pixels will also be referred to the vegetation and soil line, as described by Richardson and Wiegand (1977) and Jensen (1996). Based on that consideration, the samples was labelled as generic objects, such as 'water bodies', 'typical inundated ricefield', 'dry soils', 'shallow water', 'deeper water'. If necessary, two or three similar objects with different illumination were sampled separately, like 'forest on shaded slopes', 'forest on sunlit slopes'.

Assessment of class separability was carried out prior to the execution of classification. This was done in order to check whether or not the prepared sample classes can be separated statistically using their spectral information. In this study, class separability was computed using transformed divergence (TD), which is calculated based on divergence (D) (Jensen, 1996; ERDAS Field Guide, 1999):

$$D_{ij} = \frac{1}{2}\mathrm{tr}\,((C_i - C_i^{-1} - C_j^{-1})) + \frac{1}{2}\mathrm{tr}\,((C_i^{-1} - C_j^{-1})(\mu_1 - \mu_j)(\mu_1 - \mu_j)^T)$$

$$TD_{ij} = 2000\left(1 - \exp\left(\frac{-D_{ij}}{8}\right)\right)$$

Where :

i and j = the two signatures (classes) being compared
C_i = the covariance matrix of signature *i*
μ_i = the mean vector of signature *i*
tr = the trace function (matrix algebra)
T = the transposition function

Visual interpretation for terrain zonation

Terrain zonation was used to relate the classified pixels with their spatial-ecological context. It was assumed that each terrain unit is homogeneous in terms of its land characteristics, such as lithology/parent materials, soil texture, depth, slope steepness, and surface drainage. Under the same conditions, the same terrain units may similarly support particular rural-based uses like continuous rice fields, rubber plantation, or even in same cases may support similar urban-related functions.

To do so, a geomorphological approach was used. By this approach, the terrain is classified with respect to the parent material (lithology), relief expression, and intensity of geomorphic process or geographical site/position. A visual or photographic interpretation was carried out based on the false colour composite hardcopy image. Then, this procedure was repeated on the displayed image using on-screen digitisation technique. A geometrically corrected image was used in order to generate vector map with the same georeference as the classified and texturally transformed image. After that, the vector terrain unit map was converted to raster format for further processing.

Land-use modelling using GIS

A scenario of land-use information derivation was developed based on two thematic maps: tentative land-cover classes (which was derived from combined original and texture-filtered bands) and terrain zonation. Supported by prior knowledge of the study area and the field observation, a relationship between terrain characteristics, textural information, cover types and the detailed land-use information will be formalised into rules, which can be run in an image processing/raster GIS environment. This scenario involves Boolean logic (IF-THEN-ELSE) or in combination with matrix (tow-dimensional tables) to control thematic maps overlay process. The following approach is the example:

IF (Classified_Map Class = 'sparse vegetation on moist soil') AND
(Texture-Map Class = 'medium frequency')
THEN (IF (Terrain_Unit Class = 'valley bottom') THEN
(Final_LandUse Class = 'irrigated rice field'))

In order to keep the integrity of the final land-use classes, a nominal filter (majority filter) will be applied in 3 x 3 pixels matrix based on the spatial autocorrelation principle, so that more compact pixels of land-use classes could be derived.

Accuracy Assessment

Accuracy assessment was carried out using field data as a reference. To do so, the field data was collected during the fieldwork and mapped into a set of areas of interest (AOIs) or regions of interest (ROI). However, they were excluded from the other field dataset used for field data analysis. The ROIs were then compared with the classification result in order to create error matrices. Methods developed by Short (1982) was used to assess the classification accuracy of both six-band based and nine-band based classification results.

RESULTS AND DISCUSSION

Image Preparation and Geometric Correction

The image of the study area was extracted from a scene of Landsat TM dataset covering central part of Central Java (path/row = 120/065). The image subset was created using ENVI 3.5, by selecting the area and the number of bands. Band 6 (thermal infrared) was excluded due to its coarse spatial resolution.

As a reference for geometric correction, three sheets of topographic map at scale of 1:50,000 were scanned. The author considered the use of digital map is more useful than a manual reading of the maps in collecting ground control points (GCPs). ILWIS 3.1 software was chosen since it can be used for geometric correction of any raster image with any map object (in any format/any resolution) as reference. In order to keep the detail of the features, the topographic map was scanned at 250 dpi (dot per inch). At this resolution, the digital topographic map has nearly 5 m spatial resolution, which is considered smooth enough for this purpose.

Prior to the Landsat TM image correction, the scanned topographic map had to be geometrically corrected first, since the scanning process did not explicitly include its coordinate and projection information. Moreover, the map was scanned in patches/portions so that they need to be glued together in a digital mosaic. To do so, each patch/portion of the scanned map was rectified using its own coordinate system, which can be read on the scanned grid lines. This means that the operator only needed to click the cross between lines and entering the displayed coordinate positions. In this kind of rectification, a first order transformation (*Affine*) with around 4-10 control points was adequate to transform the flat plane (map) to another flat plane. Additional information for the rectified scanned topographic map was the projection, datum and the ellipsoid. The Universal Transverse

Mercator (UTM) projection with World Geodetic System 1984 (WGS84) datum and ellipsoid were selected. After that, the map can be glued in a mosaic for further process.

After georeferencing process, the image dataset already has a coordinate system but its resolution and north orientation still follow the older one. That is to say, the georeferencing process only fills the geometric information, without any alteration on the image characteristics. A further process, which is called *geocoding*, was needed to transform the image dataset to the corrected image. The new image would have a new characteristics, including the north orientation, pixel size (through the resampling process), and all other standard map information. By the geocoding procedure, the image of the study area was rectified and resampled to 25 m resolution. This level of resolution is also established by various agencies worldwide, such as ACRES and GeoImage (GeoImage, 2002).

Based on 40 GCPs, a RMS error = 0.383 pixels was obtained with the third order transformation. Theoretically, this RMS error level is adequate for further spatial analyses, particularly when the positional information on the image needs to be linked with other spatial data, both from other maps and field observation. However, the number of GCPs and their distribution are also important. With the first order transformation (*Affine*), 4 points are sufficient to run the equation, while with the third order, 10 points are the minimum number. By adding more GCPs that are well distributed throughout the area, a better and more accurate geocoded image can be obtained.

Textural Transformation

Image enhancement in terms of spatial filtering was applied to the image dataset. A 7x7 kernel of texture filter was used in order to transform the original pixel values to textural information within the 7x7 window. In this calculation, variance parameter was chosen instead of skewness, since the variance is more representative to show the heterogeneity of the observed pixels within the moving window.

After evaluating all 6 filtered bands, it was found that only three of them represent spectral variation relevant to this study purpose, *i.e.* band 1, band 3, and band 5 respectively. The 'new' band 3 shows clear differences in urban feature density and heterogeneity, while the difference in vegetation-related feature (such as in agricultural areas) is not accentuated. Band 5 is similar to band 4 but it gives wider range of textural information for soil-vegetation-water and soil-building-water complexes. Band 1 is more useful in representing textural information of complex land-use related to water features.

Apart from those differences, all filtered bands showed high values (that means having high variance) along the border between land-cover categories with high contrast, *e.g.* between plantation and other agricultural land, water bodies (e.g. river) and the land. Finally, only these three bands were joined with the 6 original bands in a layers stack. Thus, 9 bands were ready for further processing, consists of 6 original and 3 textural layers. In short, the texture filter also gives an *edge-effect*, even though it is not comparable with the laplacian filter.

Image Classification

In this study, a supervised approach was chosen for mapping the land-cover of the area. Multispectral classification was carried out by running the following steps: (a) preparing land-use classification scheme followed by preparing a list of possible (tentative) land cover types, (b) selecting pixel samples, and (c) executing classification. Since the immediate result of multispectral classification is a set of land-cover-related spectral classes, there is a need to transform the spectral classes to information classes. As a consequence, these three steps had to be followed by a post-classification procedure in order to transform the tentative land-cover map to land-use map.

Preparation of land-use classification scheme

Based on the prior knowledge about the area, a land-use classification scheme with 22 categories as shown on Table 1 was prepared. It should be noted, however, that the classification scheme still represents a mixed concept between 'land-cover' and 'land-use', even though efforts in making their difference clear have been made. Anyway, this study was more concentrated on the development of image processing method instead of land-use classification system, so that the prepared scheme should be accepted 'as it is'.

Based on the prepared land-use classification scheme, a list of 32 tentative land-cover classes was developed prior to and during selection of samples. As shown in table 2, the same land-cover objects with different spectral responses were labelled separately, and were considered as different classes.

Table 1. Land-use classification scheme of the study area

No.	Main category		Sub-category (to be presented on the final map)
1	1. Water-based land-use		1.1. Aqc:Aquaculture: fishponds, shrimp ponds
2			1.2. Wbd: Other water-based utilisation: reservoir, waterway, etc.
3	Agri-cultural uses with annual crops	2. Ricefield	2.1. Rf3: Ricefield: continuous (no rotation with other crops)
4			2.2. Rf2 Ricefield: rotation with other crops
5		3. Dryfield, annual crops	3.1. Dfm: Dry field with mixed crops
6			3.2. Dvg: Dry field with mainly vegetables
7		4. Dryland cultivation, mixed annual & perennial	4.1. Mxg: Mixgarden: mixed annual and perennial crops
8			4.2. Hmg: Homestead garden: mixed crops and settlement
9	5. Built-up areas: settlement and related activities		5.1. Hrs: Typical higland rural settlement, without vegetation
10			5.2. Us1: Settlement less dense, with sparse vegetation
11			5.3. Us2 Settlement dense, typical urban
12			5.4. Ucm: Commercial areas, mixed with settlement
13			5.5. Ind: Industrial areas
14			5.6. Bif: Other urban built-up areas/infrastructures
15			5.7.Ugr: Urban green and open space
16	6. Plantation: perennial crops		6.1. Tea: Tea plantation
17			6.2. Fpr: Rubber forest plantation
18			6.3. Fpt Teak forest plantation
19			6.4. Fpo: Forest plantation: others
20			6.5.Bar: Forest clearing and bare/open ground
21	7. Conservation		7.1. Cfs: Conservation: upland forest and shrubland
22			7.2. Wet Conservation: mangrove/wetland vegetation

Pixel Sampling and Statistical Evaluation of Samples

As indicated in Table 2, samples selection was done with respect to the list. Sampling procedure was applied by defining areas of interest (AOIs) with the aid of ERDAS 8.5 Imagine. Each area was defined manually by digitising the desired groups of pixels. The minimum number of pixel representing each class is 151. In this procedure, the same AOIs were applied twice, firstly to the image dataset with original bands (6 reflective bands), and secondly to the other dataset with 9 bands (6 reflective + 3 texture bands). By doing so, the same area/pixel samples can be evaluated with respect to the different sample statistics, which lead to the decision of selecting the best dataset for executing classification.

After the AOI-based sample collection, statistical evaluation of the samples was run. This was done visually by making observation on the feature space images and viewing histograms. A quantitative evaluation of the samples was also done by computing the separability between classes based on transformed divergence values. The best minimum separability between any class pair is 1984 (average) and 1019 (minimum), by taking bands 1, 4, 5, and 8 (texture-filtered band 3) at a time, if all 6 reflective plus 3 texture bands were used. For the best average separability, this setting suggests bands 1, 4, 6 (or TM band 7), and 9 (or texture-filtered band 5) with values of 1985 (average) and 1015 (minimum).

Table 2. List of tentative land-cover classes used for labelling the pixel samples

No	Tentative land-cover classes	Code	No	Tentative land-cover classes	Code
1	Deeper water bodies	Dw	17	Tea planatation-2/greening tea	Teg
2	Shallower water bodies	Sw	18	Forest vegetation on shaded slopes	Fsh
3	Typical indundated ricefield	Inu	19	Forest vegetation on neutral slopes	Fne
4	Bare ground/dry soils-1	Bs1	20	Forest vegetation on sunlit slopes	Fsu
5	Bare ground/dry soils-2	Bs2	21	Homestead garden/rural settlement	Hg
6	Bare ground/dry soils-3	Bs3	22	Dry fields with low percentage of crop cover	Df
7	Urban settlement-1	Us2	23	Cropped areas-1	Cro
8	Mixed urban settlement and commercial areas	Us1	24	Urban settlement-2 with sparse vegetation	Us1
9	Newly developed settlement	Dev	25	Shrubland	Shr
10	Typical industrial areas	Ind	26	Plantation – other crops	Plo
11	Grassland-1, healthy	Gr1	27	Typical rice-1	Ri1
12	Grassland-2, dry/mainly Imperata cylindrica	Gr2	28	Typical rice-2 mixed with other crops	Ri2
13	Forest plantation-1/teak	Tk1	29	Forest plantation-3/young rubber	Rb2
14	Forest plantation-2/rubber	Rb1	30	Forest plantation-4/younger teak	Tk2
15	Cleared forest plantation	Cf	31	Forest pnatation-5/younger teak on shaded slopes	Tk3
16	Tea plantation-1/pruned tea	Tep	32	Forest plantation-6/rubber-2	Rb3

If the setting is changed, *i.e.* by taking into account six bands at a time, the best combination of six bands for minimum separability is the one consists of bands 1, 3, 4, 6, and 9 respectively, with transformed divergence values 1990 (average) and 1372 (minimum) for minimum separability. If the best average separability is required for this setting, a combination of bands 1, 2, 4, 6, 7 and 9, which provides transformed divergence values of 1992 (average) and 1180 (minimum).

Table 3. Separability between classes as computed using transformed divergence (TD) for four-band and six-band input to classification

Criteria	TD value	The best band combination
Four bands at a time		
Best minimum separability between any class pair: - Average - Minimum	1984 1019	1, 4, 5 and 8
Best average separability between any class pair: - Average - Minimum	1985 1015	1, 4, 6, and 9
Six bands at a time		
Best minimum separability between any class pair: - Average - Minimum	1990 1372	1, 3, 4, 6, 7, and 9
Best average separability between any class pair: - Average - Minimum	1992 1180	1, 2, 4, 6, 7, and 9

Note: bands 1-6 represent reflective bands of TM1-5 and TM7 respectively, since TM6 (thermal band) was not used. Bands 7-9 represent texture-filtered bands of TM1, TM3 and TM5 respectively.

According to Jensen (1996), a transformed divergence value=2000 indicates an excellent between-class separation, while above 1900 provides good separation. In this study, all average divergence values indicate good separation between classes (above 1900). In addition, the use of texture-filtered band(s) also increases the separability between classes. Based on this quantitative evaluation, multispectral classification with six reflective plus three texture bands can be predicted to generate a better classification result, as compared to six band-based classification. Moreover, textural information contributes a better separability between classes.

Executing Classification

Multispectral classification procedure using maximum likelihood algorithm was applied following the statistical evaluation of the samples. Although it was already predicted that the use of nine bands as input to the classification would generate a better result, the procedure was also applied to another image dataset containing six reflective bands, in order to obtain a better comparison in visual aspect of the result. Figure 4 shows a comparison between the two, with two subset pair of selected areas (A and B compared with C and D).

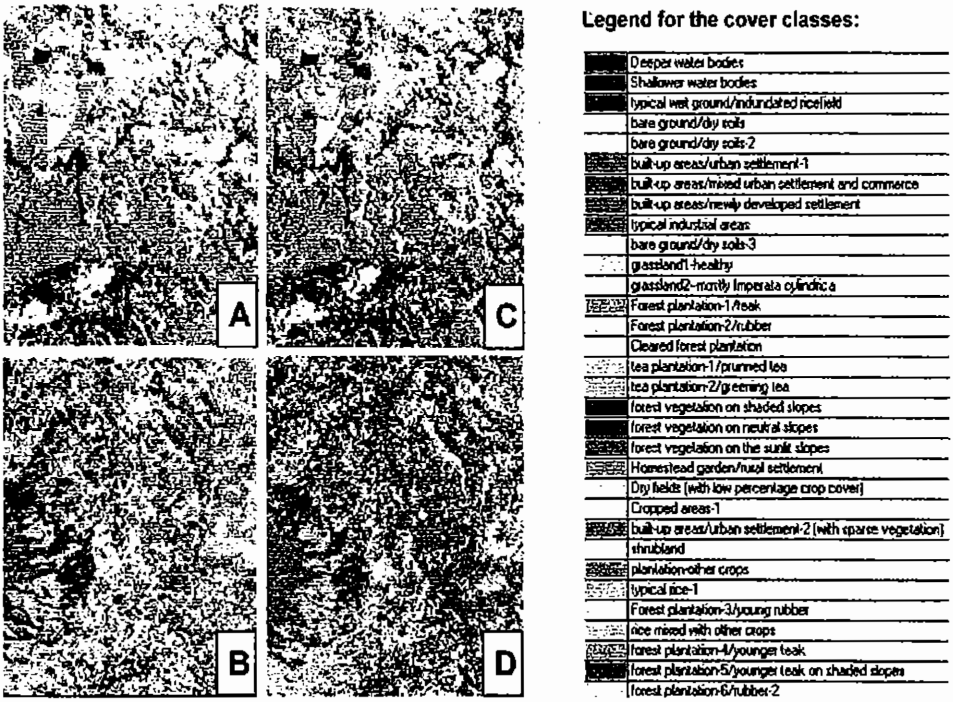

Figure 4. Classification result based on six reflective bands (TM1-5 and TM7) shown on A and B, compared with that of nine bands (TM1-5 and TM7 plus three texture filtered bands) shown on C and D. Sampling, statistical analysis of samples, and classification process were carried out using ERDAS Imagine 8.5

In general, both results are nearly the same. The spatial distribution of the spectral classes related to tentative land-cover types is almost similar. However, when a closer observation applies, the result obtained using 6 reflective bands looks more 'grainy'. The mapped land-cover types look less compact than the result obtained using 6 reflective plus 3 texture bands. On the other hand, the result derived from 9 bands shows an edge-effect, which is assigned as different tentative land-cover types. For example, the edge of 'rubber forest plantation' class is assigned as 'teak forest plantation' or even typical industrial area.

With its higher spatial integrity, the result derived from nine-band classification gives a better result than the other one; even if they were generalised using a majority filter. However, the majority filter was not applied to the classified image (particularly the better one), since this would be used in the further process, *i.e.* to be superimposed with terrain unit map. The reason behind this decision is that within a different frame setting (terrain characteristics), several different tentative land-cover types might be assigned to the same use class; or otherwise, the same tentative land-cover type that fall within different terrain units might be assigned to different land-use classes.

Visual Interpretation of Terrain/Landform Units

In order to transform the tentative land-cover classes to more meaningful information of land-use, a map containing ecological information of the area had to be prepared. The ecological information should contain a set of factors/variables having influence on the absence or presence of any land-use class. Since the study area is situated in a developing country, in which technology is not fully operated to fulfil parts of people's needs, the developed land-use categories (except urban areas) are mostly land characteristics-dependent. With respect to this consideration, the terrain unit interpretation is directed to providing mapping units related to supporting factors for land utilisation in the study area.

In this interpretation, a geomorphological approach was used, even though it was not a pure geomorphological/landform mapping. The geomorphology was only used to approach the terrain/ landscape zonation. Based on this approach, a set of terrain mapping units was derived, with names related to the landform units. Several landform units that have similar terrain characteristics related to the existing land-use were grouped together under new names. The basic principle in labelling the terrain units is that they should develop from the same geological/ lithological setting, so that the derived land characteristics including surface drainage, soil texture and depth, water availability, slope steepness, and so on. Under this set of land characteristics, some categories of land-use may be supported by a certain terrain unit but some others not.

Post Classification: Derivation of Land-use Map using Multispectral Classification Result and Terrain Unit Map

The classified image and the terrain unit map were finally used as input to further process in order to generate a land-use map. The process of combining them was carried out in a raster-based GIS environment (ILWIS 3.1), using a so-called two- dimensional table. The two-dimensional table is a matrix defined by a number of rows representing a set of classes from the first input map (*i.e.* the tentative land-cover derived from the multispectral classification) and a number of columns representing a set of classes from the second input map (i.e. the terrain unit map).

When the two-dimensional table is used to control the overlay process between the two, new attributes are defined in all cells of the matrix and they occupy the pixels of the new map. Syntax for map overlay process is given below:

LandUseMap: = TwoDimensional able [Image Based Cover Classes Map, Terrain Unit Map

Terrain unit map derived from visual interpretation

Land-cover classes derived from multispectral classification

Two-dimensional table as shown on Table 4

New Land-use map (output map)

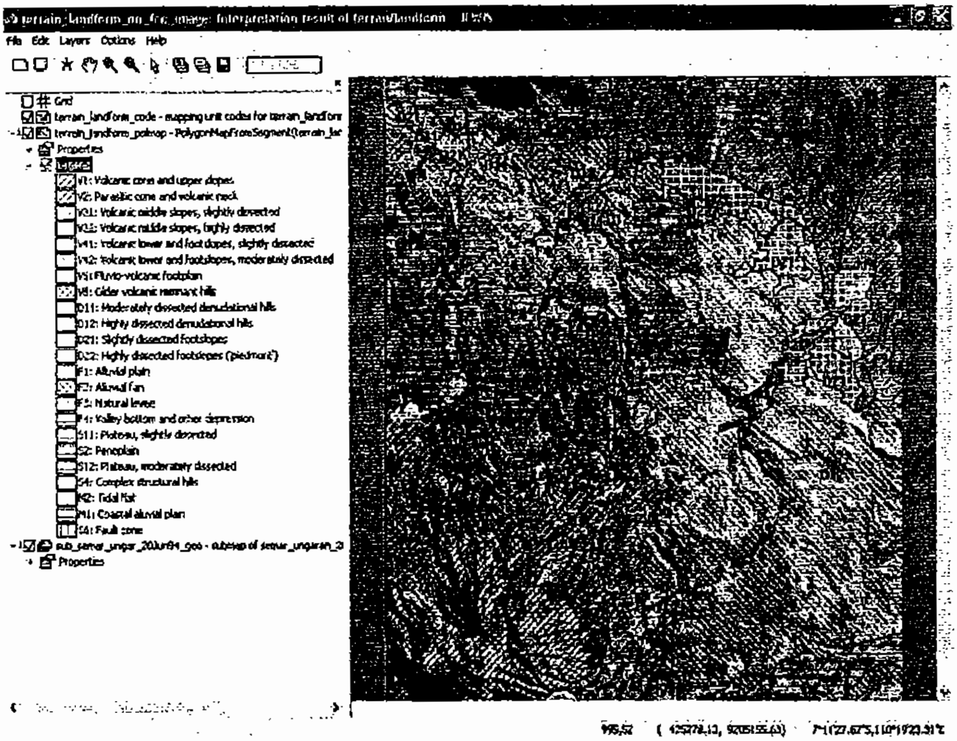

Figure 5. Screen capture of terrain unit map as a descriptor of land characteristics, to be integrated with the spectral-based land cover map and texture map. Some details on terrain/landform categorisation, which are irrelevant to land-use characterisation in the study area, were removed and merged into simpler classes. On-screen digitisation was applied using ILWIS 3.1

In defining new attributes of land-use, it was found that –in some cases—the prepared terrain unit is not sufficient (in terms of terrain zonation) to support the process. For example, the D12 (highly dissected denudational hills) should be sub-divided into two parts: the one with volcanic materials origin that derive volcanic clay soils and marine-based sedimentary materials origin that derive calcareous clay soils. The former is normally suitable for rubber forest plantation, and the later is usually occupied as teak forest plantation. In addition, with special reference to the geographical setting of the study area, the sedimentary rocks-origin landforms are closer to the coastal zone and in the eastern part, while the volcanic-origin landforms are situated in the surrounding of Ungaran volcano. The city of Semarang is situated in the coastal lowland, so that its urban expansion tends to encroach the sedimentary-origin landforms first. As a consequence, nearly all cover classes labelled with 'bare soils-1', 'bare soils-2', and 'bare soils-3' are closely related to urban land-use features such as newly developed urban areas, industrial areas, and other built-up/infrastructure areas. But if this conditional expression was applied, all dryland cultivation in the upper parts of Ungaran volcano would be misclassified as urban areas.

Geomorphologically, the use of 'denudational-origin landform" term tends to be avoided since it is still unclear in the parent material description. If the labelling is consistently applied with respect to the 'relief expression - parent material – dominant process – and or geographical site' sequence, this risk can be reduced. However, the two-dimensional table was also considered successful in diminishing the 'edge-effect' caused by the use of texture filter. As mentioned previously, the filter tends to exhibit more compact land-cover features (as compared with the use of 6 reflective bands only), but occasionally the borders between classes were accentuated so that during the multispectral classification process these pixels were misclassified to other cover types. By overlaying the tentative land-cover classes with the terrain unit map, the misclassified pixels could be returned to their correct labels.

Table 4. Terrain/landform mapping units found in the study area

No	Terrain unit	Terrain characteristics					Predominant land-use found in the unit (see the land-use classification scheme for the codes)
		Soil depth	Soil texture	Surface drainage	Surf.Wtr Availab.	Slope Steep-ness	
1	Volcanic cone and upper slopes (V1)	•	coarse	v.good	-	•••••	Cfs, Fpo, Tea, Bar,
2	Parasitic cone and volcanic neck (V2)	•	coarse	v.good	-	••••	Cfs, Hmg, Mxg
3	Volcanic middle slopes, slightly dissected (V31)	••	Moderate	Good	•	••••	Cfs, Hmg, Tea, Dvg, Hrs, Fpo
4	Volcanic middle slopes, highly dissected (V32)	•	Moderate	Good	•	••••	Hmg, Tea, Dvg, Hrs, Fpo, Fpr, Mxg, Rf3
5	Volcanic lower and footslopes, slightly dissected (V41)	••••	Mode-fine	moderate	•••	•••	Hmg, Rf3, Rf2, Dfm, Dvg, Mxg, Fpr
6	Volcanic lower and footslopes, moderately dissected (V42)	•••	Mode-fine	moderate	•••	•••	Hmg, Rf3, Rf2, Dfm, Mxg, Us1, Us2
7	Fluvio-volcanic footplain (V5)	••••	fine	Moderate -slow	••••	•	Rf3, Rf2, Mxg, Dfm, Us1, Us2
8	Other volcanic remnant hills (V6)	••	coarse	Good	•	•••	Mxg, Hmg, Dfm
9	Moderately dissected denudational hills (D11)	•	coarse	Good	-	•••	Mxg, Hmg, Dfm, Us1, Us2, Ind, Bif
10	Highly dissected denudational hills (D12)	•	v.coarse	v.good	-	•••	Hmg, Mxg, Dfm, Fpr, Fpt, Cfs
11	Slightly dissected footslopes (D21)	••	Moderate	Good	••	••	Us1, Us2, Ucm, Ind, Bif, Hmg, Mxg, Dfm
12	Highly dissected footslopes (D22)	•	coarse	Good	•	••	Us1, Us2, Hmg, Mxg, Dfm
13	Alluvial plain (F1)	•••••	v.fine	Poor	•••••	•	Rf3, , HMg, Mxg, Us1, Us2, Ucm, Ind, Bif
14	Alluvial fan (F2)	•••••	fine	Moderate-	•••••	•	Hmg, , Mxg, Rf2, Us1, Us2, Ind, Ucm, Bif
15	Natural levee (F3)	•••••	Fine-moderate	Moderate-poor	••••	•	Hmg, Mxg, Us1
16	Valley bottom and other depression (F4)	•••••	fine	Poor	•••••	•	Rf3, Rf2, Us1
17	Plateau, slightly dissected (S1)	•••	Moderate-fine	moderate	•	••	Fpr, Fpt, Hmg, Mxg, Us1, Dfm
18	Plateau, moderately dissected (S2)	••	Moderate-fine	moderate	•	••	Fpr, Fpt, Hmg, Mxg, Dfm
19	Complex structural hills 9(S4)	•	v.coarse	v.good	-	•••	Mxg, Dfm, Us1,
20	Fault zone (S6)	•	v.coarse	v.good	•	••••	Mxg, Us1, Hmg, Us2
21	Tidal flat (M1)	•	Coarse-moderate	v.poor	•••••	-	Wbd, Bif, Wet
22	Coastal alluvial plain (M2)	•••••	v.fine	Poor	•••••	•	Rf2, Ugr, Us1, Us2, Ucm, Ind, Bif,

Range for soil depth: • = shallow, ••••• = very deep. Range for surface water availability: •=very poor, •••••=very good,
Range for slope steepness: - =completely flat, • = somewhat flat, ••••• = extremely steep

TENTATIVE COVER CLASSES DERIVED FROM MULTISPECTRAL CLASSIFICATION	TERRAIN UNITS																						
	V1	V2	V31	V32	V41	V42	V5	V6	D11	D12	D21	D22	F1	F2	F3	F4	S11	S12	S2	S4	S6	M1	M2
Ba1	Fc	Cf	Df	Df	Df	Df	Rb	Df	Df	Df	U2	U2	U2	U2	Df	Rr	Df	Df	Df	Df	U1	U1	Df
Ba2	Fc	Cf	Df	Df	Df	Df	Rr	Df	Df	Df	U2	U2	U2	U2	Df	Rr	Df	Df	Df	Df	U1	U1	Df
Ba3	Fc	Cf	Df	Df	Df	Df	Rr	Df	Df	Df	U2	U2	U2	U2	Df	Rr	Df	Df	Df	Df	U1	U1	Df
Cf	Cf	Cf	Df	Df	Df	Df	Rb	Df	Df	Rb	Df	Df	Rr	Rr	Mx	Df	Tk	Df	Df	Df		Rr	Df
Cro	Fc	Cf	Mg	Mx	Fc	Fc	Aq	Mx	Mx	Mx	Df	Df	Hg	Rr	Mx	Mx	Fc	Hg	Fc	Mx		Rr	Df
Dw		Wb			Aq	Aq	Df			Wb			Wb	Wb	Wb	Wb	Wb	Wb	Wb		Aq	Aq	Wb
Df		Df	Df	Df	Df	Df	Mx	Df	Df	Df	Df	Df	Df	Df	Df	Df	Df	Df	Df	Df		Df	Df
Tk3	Te	Cf	Rb	Rb	Mx	Mx	Mx	Mx	Df	Tk	Mx	Df	Mx	Mx	Mx	Mx	Rb	Df	Df	Df		Mx	Df
Rb3	Te	Cf	Rb	Mx	Mx	Mx	Mx	Mx	Df	Tk	Df	Df	Mx	Mx	Mx	Mx	Rb	Df	Df	Df		Mx	Df
Tk2	Te	Cf	Rb	Rb	Mx	Rb	Rb	Mx	Df	Tk	Df	Df	Mx	Mx	Mx	Mx	Rb	Df	Df	Df		Mx	Df
Rb2		Cf	Rb	Rb	Mx	Rb	Rb	Mx	Mx	Rb	Df	Df	Mx	Mx	Mx	Mx	Rb	Mx	Df	Mx		Mx	Df
Tk1		Cf	Rb	Rb	Mx	Rb	Rb	Mx	Mx	Tk	Df	Df	Mx	Mx	Mx	Hg	Rb	Mx	Df	Mx		Mx	Df
Rb1		Cf	Rb	Rb	Rb	Rb	Hg	Mx	Mx	Rb	Df	Df	Mx	Mx	Mx	Hg	Tk	Mx	Df	Mx		Mx	Df
Fsw	Cf	Cf	Hg	Hg	Hg	Hg	Mx	Hg	Hg	Fo	Mx	Mx	Hg	Hg	Hg	Hg	Hg	Hg	Hg	Hg		Hg	Mx
Fsh	Cf	Cf	Hg	Hg	Mx	Mx	Mx	Hg	Hg	Fo	Mx	Mx	Hg	Hg	Hg	Hg	Mx	Hg	Mx	Hg		Hg	Mx
Fsu	Cf	Cf	Hg	Hg	Mx	Mx	Rr	Hg	Hg	Fo	Mx	Mx	Rr	Rr	Hg	Mx	Mx	Hg	Mx	Hg		Rr	Mx
Gr1	Fc	Fc	Df	Df	Df	Df	Df		Fc	Fc	Fc	Fc	Rr	Rr	Df	Rr	Df	Ug	Df	Fc	Mx	Ug	Fc
Gr2	Fc	Fc	Te	Te	Df	Df	Hg		Fc	Fc	Fc	Fc	Rr	Rr	Df	Rr	Df	Ug	Df	Fc		Ug	Fc
Hg	Cf	Hg	Hg	Hg	Hg	Hg	U1	Hg	Hg	Hg	Hg	Hg	Hg	Hg	Df	Hg	Hg	Hg	Hg	Hg		Hg	Hg
Mx	Cf	Fc	Df	Hr	Cm	Cm	U2	Mx	U1	U2	Cm	U1	Cm	Cm	Hg	U1	Cm	Cm	Cm	U1	U1	Cm	U1
Dvv	Fc	Df	Te	Hr	U2	Df	Fc	Df	U2	Fc	U2	U2	U2	U2	Cm	U2	U2	U2	U2	U2	U1	U2	U2
Plo	Cf	Fc	Hg	Fc	Fc	Fc	Rr	Fc	Mx	Hg	Mx	Mx	Mx	Mx	U2	Hg	Fc	Ug	Fc	Mx		Ug	Mx
Ri2	Fc	Df	Hr	Rr	Rr	Rr	Aq	Df	Df	Cm	Df	Df	Rr	Rr	Mx	Rc	Df	Rr	Df	Df		Rr	Df
Ws		Wb	Hr	Rc	Rc	Rc	Df		Df	U2			Rc	Rc	Df	Rc	Df	Df	Df	Df	Aq	Rr	Wb
Shr	Fc	Cf	Fc	Fc	Fc	Fc	Mx	Fc	Mx	Fc	Fc	Fc	Mx	Mx	Df	Hg	Fc	Mx	Fc	Mx		Ug	Fc
Tep	Te	Cf	Rr	Te	Df	Df	Rc	Df	Mx	Rb	Df	Df	Df	Df	Mx	Rr	Df	Mx	Df	Mx		Df	Df
Teg	Te	Cf	Rc	Te	Df	Df	U2	Mx	Mx	Mx	Df	Df	Mx	Mx	Df	Hg	Df	Mx	Df	Mx		Mx	Df
Ise	Fc	Cf	Te	Rc	Rc	Rc	Rc		Df	Df			Rc	Rc	Mx	Rc	Df	Rr	Df	Df	Aq	Rc	Wb
Isd	Fc	Cf	Te	Hr	In	In	U1	Df	U2	In	U2	In	In	In	Rc	Rr	Df	U2	Df	U2		In	In
Ri1		Cf	Rr	Rr	Rr	Rr	Rc	Mx	Df	Mx	Mx	Mx	Rc	Rc	In	Rc	Df	Rr	Df	Df		Rr	Mx
Use																							
Us2	Fc	Cf	Hr	Hr	U1	U1	U1	Df	U1	U1	U1	U1	U1	U1	U1	Rc	U1	U1	U1	U1		U1	U1
Us1	Fc	Cf	Hr	Hr	U1	U1	U2	Df	U2	U2	U2	U2	U2	U2	U2	U1	U2	U2	U2	U2		U2	U2

Codes used to indicate final land-use classes are (see Table 1):

1. Wb: other water bodies (sea, river, lake, etc.)
2. Aq: aquaculture (fishpond, shrimp pond, etc)
3. Rc: continuous ricefield
4. Rr: rice field, rotation with other crops
5. Df: dryfield with mixed crops
6. Dv:dryfield mainly with vegetables (high elevation)
7. Mx:mixgarden
8. Hg: homestead garden, mixed with rural settlement
9. Hr: highland rural settlement, no vegetation
10. Te: tea plantation
11. Rb: rubber forest plantation
12. Tk: teak forest plantation
13. Fo: other forest plantation
14. Fc: forest clearing and other open space
15. Cf: conservation, forest and shrubland
16. Cf: conservation, mangrove and other wetland vegetation
17. U1: settlement, less dense
18. U2: typical urban settlement
19. Cm: commerce areas mixed with settlement
20. In: Industrial areas
21. If: other built-up areas and infrastructures
22. urban green and open space (including city park)

Table 5. Two-dimensional table (matrix) used to control overlay process between tentative cover classes and terrain unit, in order to generate land-use information.

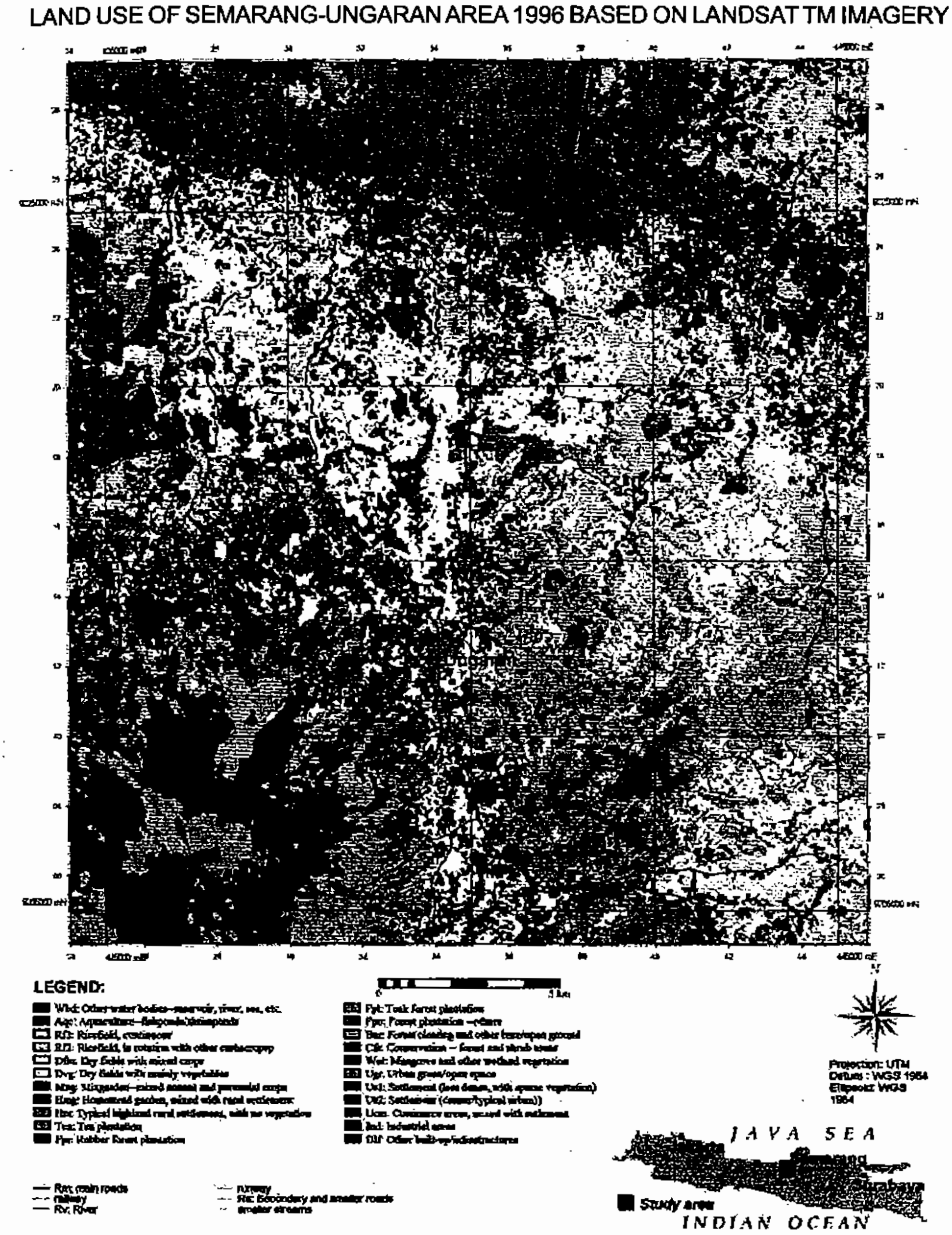

Figure 6. Final result showing land-use of the study area, which was generated from nine bands (comprising spectral and textural information) and the terrain unit map.

Another important thing to note is that the use of two-dimensional table to control post-classification process tends to create abrupt changes in adjacent land-use features. Change from one group of land-use classes (*e.g.* agricultural land-use classes) to another one coincides with the change in terrain/landform units. Since the two-dimensional table works on the basis of Boolean logic (IF-THEN-ELSE), this disadvantage comes up as its consequence and can only be reduced by defining transitional terrain units, unless other methods (*e.g.* fuzzy, Dempster-Shafer Theory of Evidence) are used.

Accuracy Assessment of the Land-use Map

Accuracy assessment using confusion matrix was applied to both six-band based and nine-band based classification results. To do so, 647 pixels were evaluated with respect to field reference. It was found that by using six reflective bands as classification input, an overall accuracy of 88.71% was obtained. With nine bands including three texture-filtered bands as the input, the overall accuracy was 93.34% that means the introduction of textural information increased the classification accuracy. As discussed previously in Section 5.3.2, the transformed divergence values increase with the involvement of texture-filtered bands and the accuracy assessment result has thus proven a parallel finding.

However, a closer look to the accuracy level of individual classes showed slight differences. It was found that land-use categories such as plantations tend to show lower accuracy level in nine-band based classification result (*e.g.* 89.44% for ruber plantation, as compared with 92.37% for the same category resulted by six-band classification). This is probably due to the 'edge effect' resulted by the texture filtering process. High accuracy level was found primarily on urban features and mosaic of rice fields or mix garden. These categories consistently showed higher accuracy level, *e.g.* 94.22%, 94.10%, and 93.82% for industrial areas, typical denser urban settlement, and commerce areas mixed with settlement respectively, in comparison with accuracy levels of corresponding categories (91.52%, 86.76%, and 88.21%) generated by six-band based classification. This means that textural information may significantly increase the classification accuracy in built up areas.

Next Agenda/Further Studies

This study has demonstrated the development of image processing method, which incorporates spectral, textural, and ecological information in order to generate more detailed land-use information. Methodologically, there are some other aspects to be considered for a better result, and they may be included in the next/further studies:

1. With the increase of very high-resolution images availability (IKONOS, QuickBird, IRS-Pan, and SPOT-5), the textural information becomes more important so that they can be used in combination with the lower spatial resolution images, or can be used separately. This study used the same spatial resolution to define textural information of the neighbourhood pixels, but by incorporating a higher spatial resolution image (even using scanned aerial photographs), the textural information within the lower spatial resolution image can be defined, so that the 'edge-effect' on the final result can be minimised or be removed

2. The use of terrain unit information with 'crisp' boundaries tends to force the image pixels to fall within the terrain units with predefined land-use classes. Since the boundaries of many geographical objects are basically fuzzy (Burrough and Frank, 1996), the use of Boolean logic breaks the fuzzy nature. In order to improve the result, the terrain units with crisp boundaries may be transformed to the ones having fuzzy boundaries. To do so, knowledge about the imprecision and fuzziness of the borders between units can be used to develop raster-based 'fuzzy borders' based on a distance calculation from the defined/ digitised borders. This method may improve the quality of the terrain units into a new map with gradual change from one unit to another.
3. Fuzzy approach may be applied to improve the classification result. The use of multisource evidential approach based (Srinivasan and Richards, 1990; Peddle and Franklin, 1992; Danoedoro, 1993; Richards, 1993) can be used to combine the classified image and the terrain unit map.
4. Conceptually, the classification scheme used in this study may also be improved (to be made more detailed) to support efforts in making land-use information as a surrogate variable for various environmental applications in the study area.

CONCLUDING REMARKS

This study was a small project addressed to an exploration on the potentials of the use of multisource information in image classification, so that more detailed land-use categorisation may be achieved. Based on the study that has just been done, some potential to be explored further were found; but some limitations were also recognised.

1. In general, the use of textural information as an additional layer in multispectral classification increases the capability of statistical separation of samples. Three selected texture-filtered bands in combination with 6 reflective bands enable the analyst to label pixels with subtler categories of land-cover related to land-use. The introduction of textural layers in multispectral classification also derive better, more compact cover classes, even though a kind of spatial effect at the edges (edge effect) occasionally comes up,
2. The use of ecological information in terms of terrain/landform units can improve the classification result, by transforming the tentative land-cover classes to the final land-use categories. Besides, the terrain units are also useful in edge-effect removal. However, the use of Boolean logic to control the map overlay between the tentative land-cover and the terrain unit is considered too rigid,
3. This study also gives opportunity to carry out further studies, concentrating on (a) development of image-based land-use classification to be used as surrogate variable in various environmental applications, and (b) methods in extracting land-cover/land-use information using various sources and various spectral/spatial resolutions. The use of fuzzy boundaries in defining terrain units and textural information from higher spatial resolution images are prioritised.

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