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Full Length Research Paper

Integrated method to extract information from high and very high resolution RS images for urban planning

D. Amarsaikhan[1]*, M. Ganzorig[1], H. H. Blotevogel[2], B. Nergui[1] and R. Gantuya[1]

[1]Institute of Informatics and RS, Mongolian Academy of Sciences, av. Enkhtaivan-54B, Ulaanbaatar-51, Mongolia.
[2]Dortmund University of Technology, Faculty of Spatial Planning Institute of Spatial Planning, August-Schmidt-Str. 10, D-44221 Dortmund, Germany.

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The aim of this research is to propose an integrated methodology for the extraction of information from high and very high resolution satellite images and also to demonstrate how the extracted information can be used for urban area studies. For the information extraction, three different approaches such as interpretation, automatic and artificial intelligence methods are used. As the interpretation method a visual interpretation is used, whereas as the automatic method a refined maximum likelihood classification that uses spatial thresholds defined from the local knowledge is applied. For the artificial intelligence method, a rule-based algorithm which consists of a set of rules, containing an initial image segmentation procedure as well as the constraints on spectral parameters and spatial thresholds is constructed. Overall, the research indicates that the high and very high resolution satellite images can be successfully used for general and detailed urban studies and the proposed methods can be efficiently used for the extraction of accurate thematic information.

Key words: Interpretation, automatic, artificial intelligence, urban study, satellite image.

INTRODUCTION

Recently, cities all over the world have experienced rapid growth because of the rapid increase in world population and the irreversible flow of people from rural to urban areas. Specifically, in the larger towns and cities of the developing world, the rate of population increase has been constant and nowadays, many of them are facing unplanned and uncontrolled settlements at the densely populated sites or fringes (Amarsaikhan et al., 2001. 2006) . Mongolia, as many countries of the developing world has problems with the urban expansion and the growth of population in the main cities. For example, over the last two decades Ulaanbaatar, the capital city of Mongolia has experienced different urban related problems. In the city, various problems had been previously accumulated during the centralized economy and they have been intensified by the reforms of the entire political and economic systems, unregulated market development and the rapid population growth caused mainly by migration from rural areas (Amarsaikhan et al., 2005).

To analyze the rapid changes, urban planners and decision-makers need to have the detailed integrated spatial data sets compiled within a geographical information system (GIS). However, most city planners, especially from developing countries, have a lack of the integrated spatial information relevant for current decision-making (Amarsaikhan and Sato, 2003; Amarsaikhan et al., 2009a) . In urban context, spatial information can be collected from a number of sources such as city planning maps, topographic maps, digital cartography, thematic maps, global positioning system, aerial photography and remote sensing (RS). Of these, only RS can provide real-time information that can be used for the real-time spatial analysis. Over the past few years, RS techniques and technologies, including system capabilities have been significantly improved. Meanwhile, the costs for the primary RS data sets have drastically decreased (Amarsaikhan et al., 2006).

In general, the scale of the thematic information to be extracted from digital RS data is dependent upon the spatial resolution of the acquired images. To get an acceptable ac-

*Corresponding author. E-mail: amar64@arvis.ac.mn. Tel: 976-11-453660. Fax: 976-11-458090

curacy for the selected map scale using optical images it is desirable to include at least 20 - 25 pixels per centimeter; however, these numbers may change depending on the purposes of the study as well as the requirements of conducted projects (Amarsaikhan and Sato, 2003). The standard high resolution satellite data sets such as Landsat and SPOT allow the mapping specialists to map the natural and man made features usually at a class level and it is very difficult to define the individual objects on such images. However, using very high resolution RS images such as Quickbird and Ikonos it is possible to map any features at object as well as class levels. This means that it is possible to extract from RS images, different thematic information of varying scales to be used for rapid urban related decision-making processes (Amarsaikhan et al., 2009b).

Over the years, for the extraction of thematic information from either multispectral or multisource RS images at class level, different image processing techniques have been used. Most of these techniques were based on digital methods of classification which mainly included statistical and non-statistical methods, neural networks and decision tree methods as well as Dempster -Shafer theory of evidence and other knowledge-based classifications (Solberg et al., 1996, Amarsaikhan, 1997; Gamba and Houshmand, 2001; Linderman et al., 2004, Amarsaikhan et al., 2007) . In recent years, for the identification of indivi-dual objects from the very high resolution satellite images different object-oriented classification techniques have been developed (Giada et al., 2003; Lucieer, 2008). However, it is still very difficult to extract reliable information about objects as they are positioned in the real world.

The aim of this study is a) to propose an integrated method for the extraction of land use/cover information from high and very high resolution satellite images and, b) to demonstrate how the extracted information can be used for urban studies. To extract the urban land use infor-mation at an object level, a visual interpretation has been applied, whereas for the extraction of information at a class level, automatic and artificial intelligence methods have been used. For the final analyses, multi-source satel-lite images with different spatial resolutions as well as topographic maps of varying scales have been compiled within Erdas Imagine 9.1 and ArcGIS 9.2 systems and different RS and GIS techniques were applied.

TEST SITE AND DATA SOURCES

As a test site, Ulaanbaatar, the capital city of Mongolia has been selected. Ulaanbaatar is situated in the central part of Mongolia, on the Tuul River, at an average height of 1350m above sea level and currently has over 1 million inhabitants (National Statistical Office of Mongolia 2009). The city is extended from the west to the east about 30km, and from the north to the south about 20km. Founded in 1639 as a small town named Urga, today it has prospered as the main political, economic, business, scientific and cultural centre of the country. Figure 1 shows a Landsat ETM+ image of the test site, and some examples of its land cover.

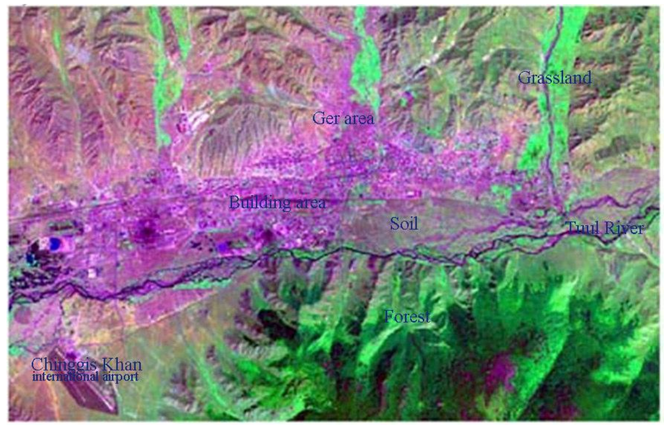

Figure 1. 2001 Landsat ETM+ image of Ulaanbaatar.

In the present study, the data used consisted of bands 4,5 and 7 of Landsat MSS data of 1974 with a spatial resolution of 79 m; bands 2, 3 and 4 of Landsat TM data of 1990 with a spatial resolution of 30m; multispectral SPOT XS image of 1997 with a spatial resolution of 20 m; bands 2, 3 and 4 of Landsat ETM+ image of 2001 with a spatial resolution of 28 m; multispectral SPOT 5 image of 2002 with a spatial resolution of 4 m; panchromatic Quick-bird image of 2002 with a spatial resolution of 0.63 m; a topographic map of 1984 of scale 1:50.000; a topographic map of 2000 of scale 1:5.000 as well as JERS-1 L- band synthetic aperture radar (SAR) intensity image of 1997 with a spatial resolution of 18m. In addition, census data of 2002 related to the Ulaanbaatar city was available (Mongolian Statistical Year Book 2002).

ANALYSES AND DISCUSSION

In the present study, an integrated method to extract information from high and very high resolution RS data sets has been proposed. The method contains three different approaches such as (visual) interpretation, automatic and artificial intelligence. Each of these methods together with a related case study is discussed in detail below.

Interpretation method

Any visual interpretation using RS data can be considered as an interpretation approach. This is the most widely used method for extracting thematic information or updating various layers of a GIS. For example, in urban areas land use types can be directly digitized on the RS images thus producing a new map, meanwhile updating a digital data-base stored within a GIS. To demonstrate this approach, a residential apartment quarter (that is 40.000 area) located in central part of Ulaanbaatar city has been selected and for the detailed analysis, SPOT 5 and Quickbird images of 2002 have been used.

Georeferencing and enhancement of the multi-sensor images: Initially, the SPOT 5 and Quickbird images have been georeferenced to a Gauss-Kruger map projection, using a topographic map of 2000, scale 1:5.000. The ground control points (GCPs) have been selected on well defined intersections of roads and for the transformation, a linear transformation and nearest neighbour resampling approach have been applied. The root mean square (RMS) error of the image transformation for the SPOT 5 image was 0.97 pixel, while for the Quickbird image it was 0.99 pixel. In each case of the georeferencing, an image was resampled to a pixel resolution of 0.7 m.

Then, in order to enhance the spectral and spatial variations of different land use classes as well as to merge the images with different spatial resolutions, some image fusion techniques have been applied. The image fusion is the integration of different digital images in order to create a new image and obtain more information than can be separately derived from any of them. In the present study, such fusion methods as Brovey transform, intensity-hue-saturation (HIS) transformation and prince-pal component analysis (PCA) have been applied and compared. Brovey transform is a simple numerical method used to merge different digital data sets. The algorithm based on a Brovey transform uses a formula that normalises multispectral bands used for a red, green, blue colour display and multiplies the result by high resolution data to add the intensity or brightness component of the image (Vrabel, 1996). The IHS transform is defined by three separate and orthogonal attributes, namely intensity, hue and saturation. Intensity represents the total energy or brightness in an image and defines the vertical axis of the cylinder. Hue is the dominant wavelength of the colour inputs and defines the circumferential angle of the cylinder. Saturation is the purity of a colour or the amount of white light in the image and defines the radius of the cylinder (Harris et al., 1990). In the HIS each pixel is represented by a three-dimensional coordinate position within a colour cube. Pixels having equal components of red, green and blue lie on the grey line, a line from the cube to the opposite corner. PCA is a statistical technique that transforms a multivariate data set of intercorrelated variables into a set of new uncorrelated images called principal components or axes. The procedure involves a linear transformation so that the original brightness values are re- projected onto a new set of orthogonal axes. This method is helpful for image encoding, enhancement, change detection and multitemporal dimensionality (Pohl and Van Genderen, 1998).

Before applying the fusion techniques, a 5 x 5 size high pass filtering (Gonzalez and Woods 2002) has been applied to the panchromatic image in order to enhance the edges. After the georeferencing, the images were merged using the above mentioned fusion methods. For the Brovey transform, the bands of SPOT 5 were considered as multi-spectral bands, while Quickbird image was considered as higher spatial resolution band. For the IHS transfor-mation, the red, green and blue (RGB) image created by green and near infrared bands of the SPOT 5 data as well as panchromatic band of Quickbird data have been used and the panchromatic band was considered as the I. When the IHS image was transformed back to the RGB colour space, contrast stretching has been performed to the I channel. PCA has been performed using the available panchromatic and multispectral bands. As it was seen from the PCA, the first three PCs contained almost 99% of the total variance. The inspection of the last PC indicated that it contained noise from the total dataset. Therefore, it was excluded from the final analysis.

Interpretation and analysis: In order to obtain a reliable color image that can illustrate the spectral and spatial variations in the selected residential land use classes, different band combinations have been used and compared. Although, the image created by the Brovey transform contained some shadows that were present on the panchromatic image, it still illustrated good result in terms of separation of the available land use classes. The images created by the IHS and PCA methods contained less shadows, however, it was very difficult to analyze the final images, because they contained too much color variations of objects belonging to the same class. There-fore, for the interpretation of the selected land use types, the image created by the Brovey transform has been used. On the Brovey transformed image, the selected land use types have been digitized using ArcGIS system. Then, for each of the land use types the related analysis has been carried out. The Brovey transformed image of SPOT 5 and Quickbird as well as the interpreted image are shown in Figure 2a and b.

As seen from the result of the interpretation, in this area, residential apartments occupy 3.18 ha or 43.7%, the offices and establishments occupy 1.95 ha or 27%, trade and service facilities occupy 0.36 ha or 5%, general educational school and kindergarten occupy 0.21 ha or 3%, printing industry occupies 0.2 ha or 2.7%, roads and squares occupy 1.37 ha or 18.8% of the entire land use. The coverage density in this area constitutes 41.6% and the average population density equals 126 persons per ha. The land designated for offices and establishments, trade and services, production and manufacturing represent new types of the land use emerged during the transition period. These new types of the land use in the course of their emerging had caused alteration to the primary apartment functions in the given region. In general, the commercialization process in this area has been increased and the trends leading to the deterioration of comfortable living conditions of the residents have been observed. For example, the ground floors of the apartment buildings have been transferred to the ownership of different services such as retail sales, saloons, cafeteria, bars, sauna and karaoke. Moreover, intentional alterations of the building and construction structures caused a negative influence on the comfort-able living conditions of the residents in the apartment

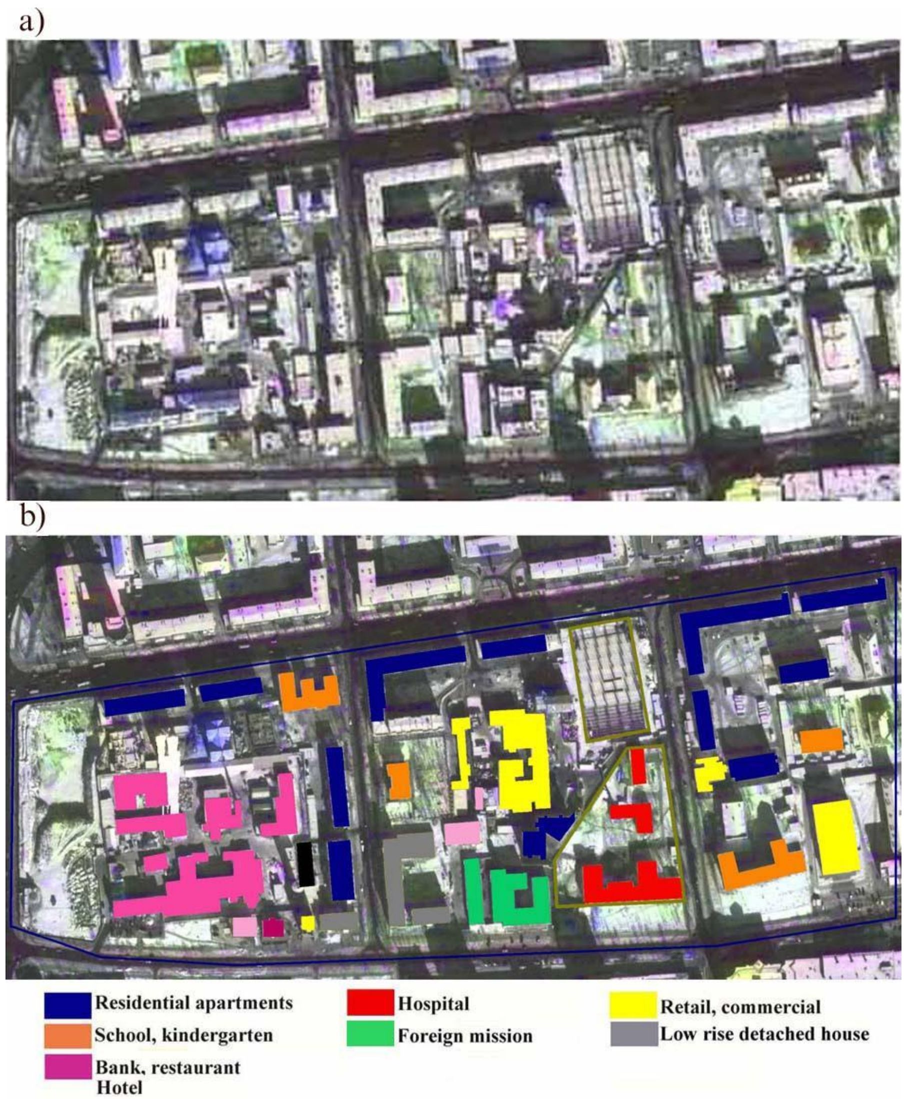

Figure 2. The images created by Brovey transform (a) and the related interpretation (b).

houses.

Automatic method

In this method, thematic information should be auto-matically generated after applying some image processing techniques. Although, there are many techniques of digital image processing used to automatically extract thematic information, the most techniques applied in urban context are used for linear feature extraction and land use map generation. For the linear feature extraction different filtering techniques, ratios and their combinations can be used, while for the land use map generation various statistical and non-statistical classification methods and their combinations could be applied (Benediktsson et al., 1997, Duda et al., 2001).

Within the framework of this research, as a case study of the automatic approach land cover mapping has been performed and evaluation of the urbanization process of Ulaanbaatar city has been carried out using multi-temporal RS images. As RS data sources, Landsat MSS, Landsat TM, SPOT XS and Landsat ETM+ data were used. To extract the urban land cover information from the selected RS data sets, a maximum likelihood classification that uses spatial thresholds defined from the local knowledge was applied.

Radiometric correction and georeferencing of the multispectral images: At the beginning, all images were thoroughly analyzed in terms of radiometric quality and geometric distortion. The Landsat MSS data had a destriping effect and it was corrected by applying a destrip removing function followed by a 3 x 3 size average filtering (Benediktsson and Sveinsson, 2003). Then, the RS images were successively georeferenced to a Gauss-

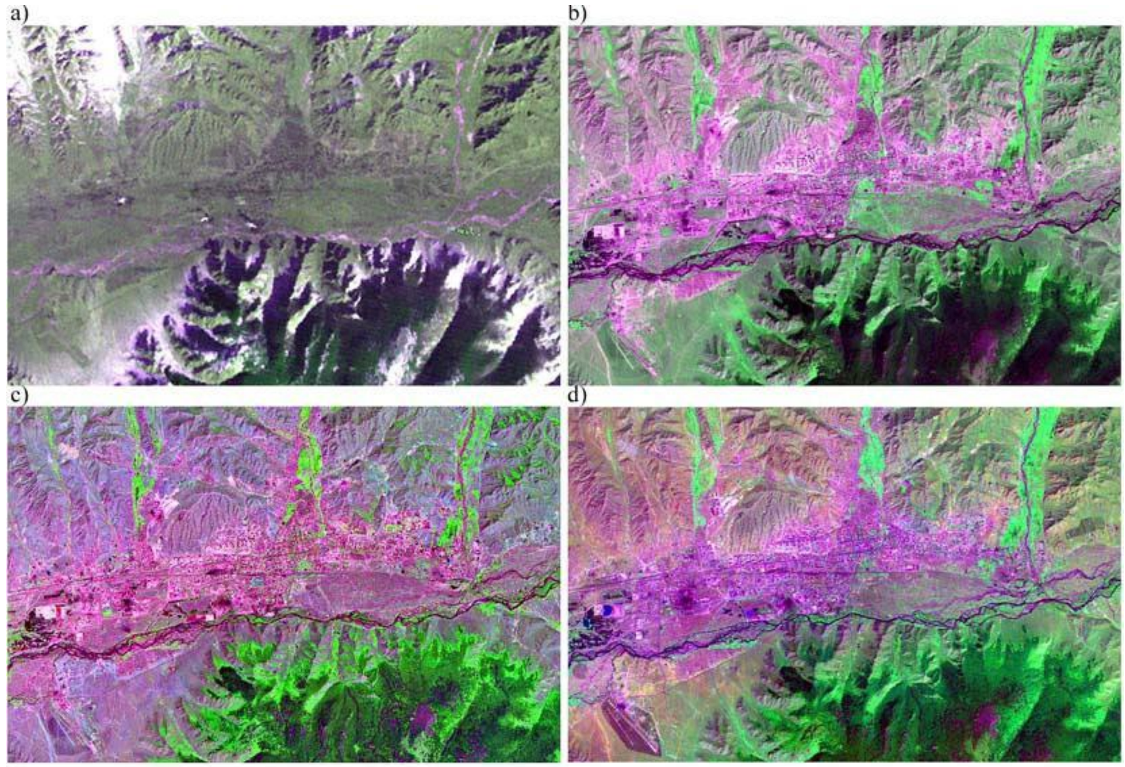

Figure 3. RS images of Ulaanbaatar area. a) MSS image of 1974, b) TM image of 1990, c) SPOT XS image of 1997, d) ETM+ image of 2001.

Kruger map projection using a topographic map of 1984. For each image, 10 GCPs have been selected on well defined cross sections of roads, streets and other clearly delineated sites. For the actual transformations, a second order transformation and nearest neighbour resampling approach (Mather 1999) were applied. The RMS errors of the image transformations were 1.2 pixels for the MSS, 0.92 pixels for the TM, 0.65 pixels for the SPOT XS and 0.84 pixels for the ETM+, respectively. In all cases of the georeferencing, an image was resampled to a pixel resolution of 30 m. Figure 3 shows the test area in the selected RS images.

Classification of the images and evaluation of the urbanization: To extract the reliable urban land cover information from the selected RS data sets, a refined maximum likelihood classification that uses spatial thresholds defined from the local knowledge has been used (Amarsaikhan et al., 2006). As the features for the classification, for all data sets green, red and near infrared bands have been selected. To define the sites for the training signature selection, from the images, several areas of interest have been selected for the available classes such as building area, ger (Mongolian national dwelling) area, green vegetation, soil and water using the local knowledge. Then, the separability of the selected training signatures was evaluated using Jeffries- Matusita distance and the samples demonstrated the best possible separability were chosen to form the final signatures. The final signatures included 512 pixels for building area, 485 pixels for ger area, 454 pixels for green vegetation, 428 pixels for soil and 86 pixels for water.

For the actual classification, a maximum likelihood classification (Richards and Xia 1998) has been used. The maximum likelihood classification is the most widely used supervised classification technique, because a pixel classified by this method has the maximum probability of correct assignment (Erbek et al., 2004). The decision rule can be written as follows:

$$P(Ci|x) = P(x|Ci)*P(Ci)/P(x)$$

Where; $P(Ci|x)$-posterior probability, $P(x|Ci)$-conditional pro-bability, $P(Ci)$-prior probability, $P(x)$-probability of finding a pixel from any class. The actual classification is performed according to $P(Ci|x) > P(Cj|x)$ for all j#i.

Initially, in order to check the performance of the standard method, the selected bands were classified, however, on the classified images there were different mixed classes and it was not possible to correctly evaluate the urbanization process. To separate the statistically mixed classes, the class specific features as well as spatial thresholds can be applied. The class specific features can be determined through the feature extraction process; however, the application of this approach would become difficult if there is a fewer number of bands. The spatial thresholds can be defined from the knowledge about the test area or historical GIS data sets. The idea of the spatial threshold is that it uses a polygon boundary to separate the overlapping classes and only the pixels falling within the threshold boundary are used for the classification. In that case, the likelihood of the pixels to be correctly classified will significantly increase, because the pixels belonging to the class that overlaps with the class to be classified using the threshold boundary are temporarily excluded from the decision making process. In such a way, the image can be classified several times using different threshold boundaries and the results can be merged (Amarsaikhan and Sato 2004).

In the present study, to separate the statistically overlapping classes, different spatial thresholds determined on the basis of the local knowledge have been used. The local knowledge was based on the knowledge about the site as well as the historical GIS data sets. A general diagram of the refined classification is shown in Figure 4 and the results of the classifications using the defined spatial thresholds are shown in Figure 5. For the accuracy assessment of the classification results, the overall performance has been used. This approach creates a confusion matrix in which reference pixels are compared with the classified pixels and as a result an accuracy report is generated indicating the percentages of the overall accuracy (ERDAS 1999). As ground truth information, different AOIs containing the purest pixels have been selected. The confusion matrices produced for the refined classification method indicated overall accuracies of 87.2% for the 1974 data, 90.9% for the 1990 data, 93.2% for the 1997 data and 91.5% for the 2001 data, respectively.

In order to define the areas related to urban expansion, initially, the total areas related to each class was defined by calculating statistical parameters of the classified multitemporal RS images.

Then, the classes were merged into two classes: urban and non-urban. The urban class included building area and ger area, whereas non-urban class included green vegetation, soil and water classes. The areas related to urban class evaluated from RS images obtained at different years are shown in Table 1. As seen from Table 1, urban area in Ulaanbaatar city covered 5217.1ha in 1974, 9033.1ha in 1990, 9497.3ha in 1997 and 9687.8ha in 2001, accordingly. This means that in recent decades Ulaanbaatar city has faced very rapid urbanization process and its size has been almost doubled since 1974. This information together with other data (e.g., census) can be successfully used for studies of general urban expansion in relation to a population growth.

Artificial intelligence method

Unlike the other methods which are executed either automatically or by analyst's intuition, in this method structured knowledge based on human expertise is used

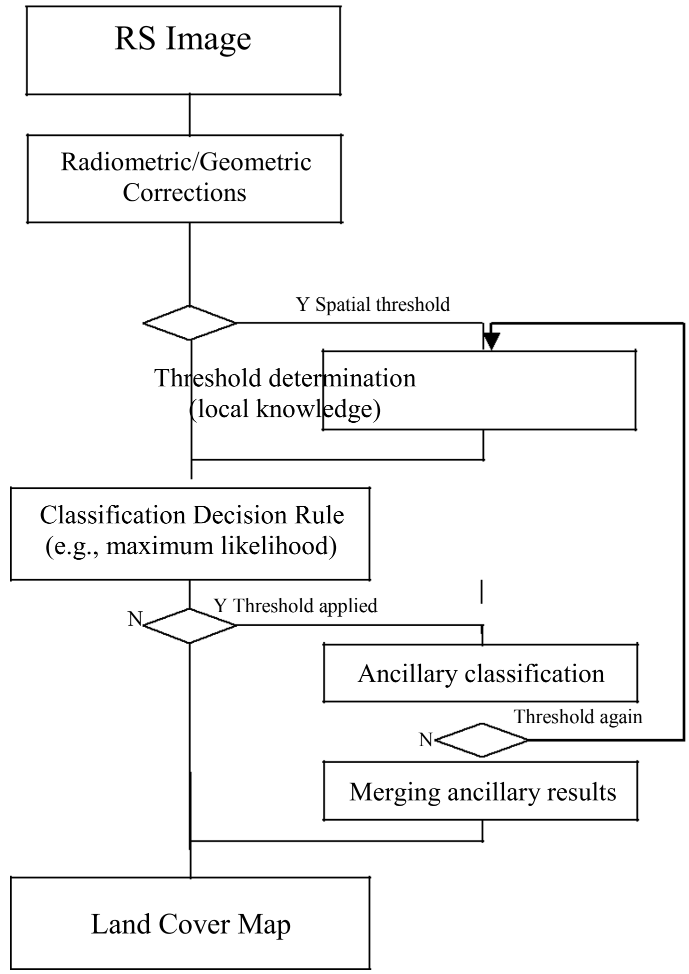

Figure 4. A general diagram for the refined classification.

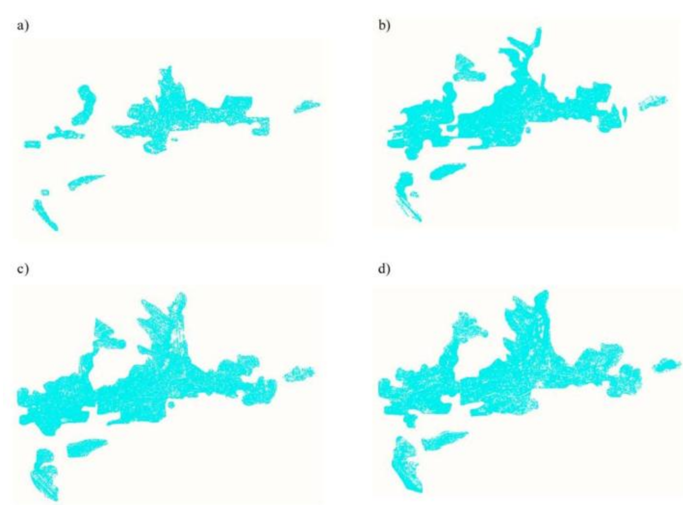

Figure 5. The results of the classifications of a) MSS image of 1974, b) TM image of 1990, c) SPOT XS image of 1997, d) ETM+ image of 2001 (cyan represents urban area and white represents non-urban area).

Table 1. The total areas for urban class in different years, evaluated from multitemporal RS data sets.

RS images	Total areas in hectares
Landsat MSS (1974)	5217.1
Landsat TM (1990)	9033.1
SPOT XS (1997)	9497.3
Landsat ETM+ (2001)	9687.8

for automatic image interpretation. In recent years, application of a knowledge-based approach in digital image processing has been of great interest. Different types of this approach have been, and are being developed for the information extraction from RS images representing knowledge in different ways. The most commonly used knowledge representation technique is the production rule type that is based on different rules whose conditions have to be fulfilled under certain constraints (Du and Lee, 1996; Benediktsson et al., 1997; Lawrence and Wright, 2001; Amarsaikhan et al., 2007).

Within the framework of this research to demonstrate a case of the artificial intelligence, for the information extrac-tion, a similar approach of a rule-based method applied in Amarsaikhan et al. (2007) has been used. A rule-based approach uses a hierarchy of rules, or a decision tree describing the conditions under which a set of low level primary objects gets abstracted into a set of the high level object classes (Amarsaikhan and Douglas, 2004). The primary objects contain the user-defined variables and include geographical objects represented in different structures, external programs, scalars and spatial models (Erdas, 1999). As a case study of this approach, land cover mapping has been performed integrating multi-source RS data sets. The selected part of the capital city is characterized by such classes as building area, ger area, forest, grassland, soil and water.

The constructed rule-based approach consists of a set of rules, which contains the initial image segmentation procedure based on a Mahalanobis distance rule and the constraints on spectral parameters and spatial thresholds. In the Mahalanobis distance estimation, for the initial separation of the classes, only pixels falling within 1.5 SD and the features extracted through a feature extraction process, were used. As the reliable features in which the selected classes could be more separable, the PCs extracted through the PCA have been chosen. The PCA has been performed using 4 bands, including the SPOT XS as well as JERS-1 SAR data sets. Before the PCA, to reduce the speckle of the radar images, a 3 x 3 gamma map filtering (Serkan et al., 2008) was applied to the JERS-1 SAR image. The result of the PCA is shown in Table 2.

As seen from Table 2, in the PC1 that contains 54.58% of the overall variance, visible green and red bands of SPOT XS have high loadings, whereas in the PC2 that contains 32.10% of the overall variance, JERS-1 SAR has a very high negative loading.

Table 2. Principal component coefficients from the SPOT XS and SAR bands.

	PC1	PC2	PC3	PC4
XS1	0.625	0.187	-0.213	0.726
XS2	0.657	0.155	-0.269	-0.685
XS3	0.293	0.215	0.930	-0.035
JERS-1	0.299	-0.945	0.125	0.023
Eigenvalue	6715.60	3949.53	1521.71	117.58
Variance %	54.58	32.10	12.37	4.49

In the PC3 that contains 12.37% of the overall variance; near infrared band of SPOT XS has a very high loading, while in the PC4 that contains 4.49% of the overall variance, red band of the SPOT XS has a high loading. However, the inspection of the PC4 indicated that it contained noise from the total data set. Therefore, for the final features, PC1, PC2 and PC3 have been chosen. For the initial image segmentation, these selected features were evaluated using a Mahalanobis distance rule. The decision rule can be written as follows:

$$MD_k=(x_i- m_k)^t\, V_k^{-1}(x_i- m_k) \qquad (2)$$

Where; x_i is the vector representing the pixel, m_k is the sample mean vector for class k, and V_k is the sample variance-covariance matrix of the given class.

Here, if SD(x) $\geq$ 1.5, then a pixel (x) is assigned to the class where MD_k is the minimum.

The pixels falling outside of 1.5 SD were temporarily identified as unknown classes and further classified using the rules in which different spectral and spatial thresholds were used. The spectral thresholds were determined based on the knowledge about spectral and scattering characteristics of the selected six classes, whereas the spatial thresholds were determined using polygon boundaries separating the overlapping classes. The flowchart for the constructed rule-based approach is shown in Figure 6 and the image classified by this method is shown in Figure 7. As seen from the image, the rule-based approach could very well separate all classes, specifically the statistically overlapping classes: building area and ger area. The overall classification accuracy has been evaluated using a set of pixels selected from the regions that contained the purest pixels and it demonstrated an overall accuracy of 92.87%.

The areas related to each class evaluated from the rule-based method are shown in Table 3. The extracted information can be integrated with other thematic information and used for different urban related studies.

Conclusions

The aim of this study was to propose an integrated metho-

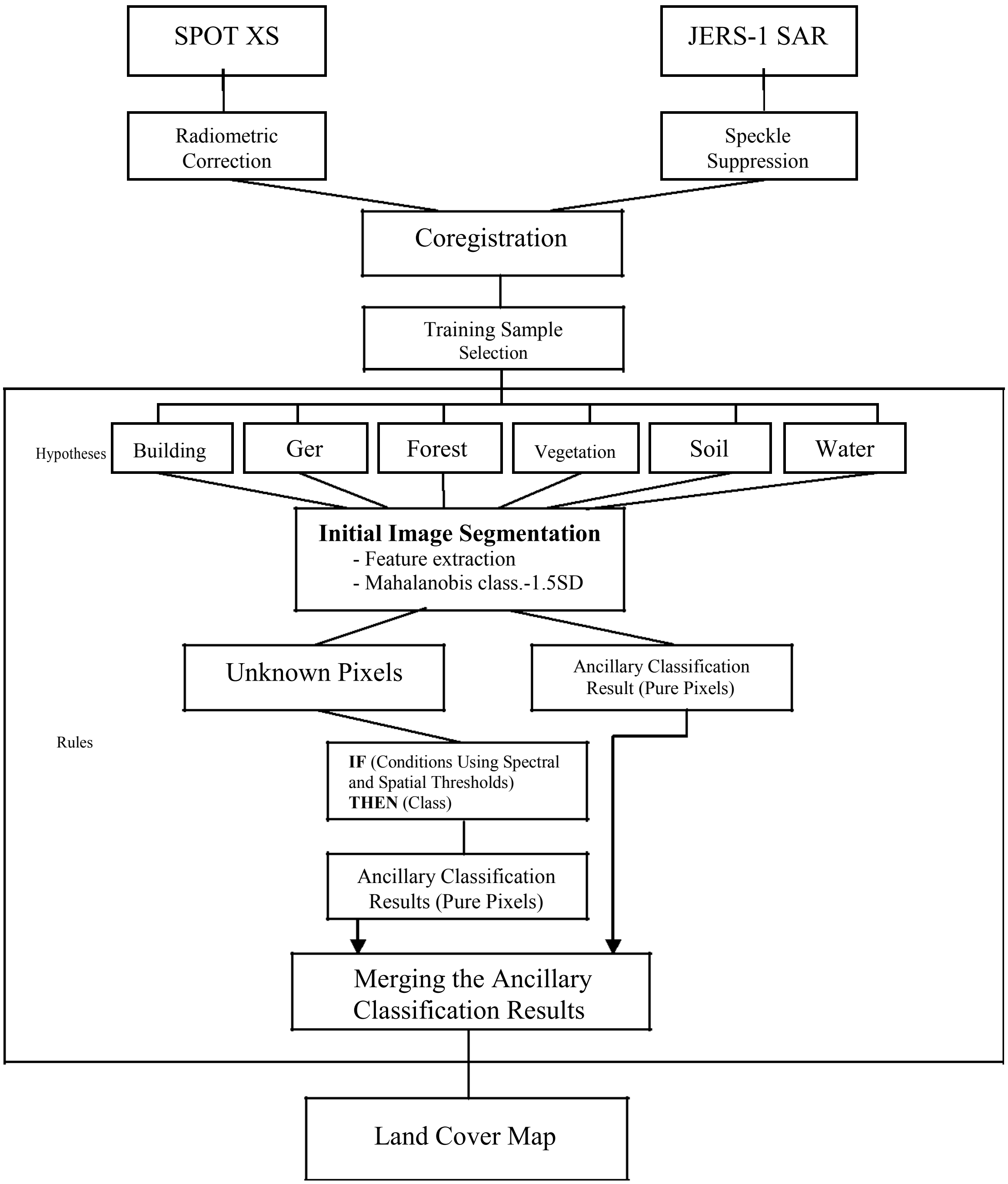

Figure 6. A general diagram for the rule-based classification.

dology for the extraction of information from high and very high resolution satellite images and also to demon-strate how the extracted information can be used for urban studies. For the information extraction, three differ-rent approaches such as interpretation, automatic and artificial intelligence methods were suggested. As the inter-pretation method a visual interpretation was applied, whereas as the automatic method a refined maximum likelihood classification that uses spatial thresholds defined from the local knowledge was used. For the artificial intelligence method, a rule-based algorithm which consists of a set of rules, containing an initial image segmentation procedure as well as the constraints on spectral parameters and spatial thresholds was con-structed. For each of the proposed methods, a related case study was conducted. For the analyses, multi-source

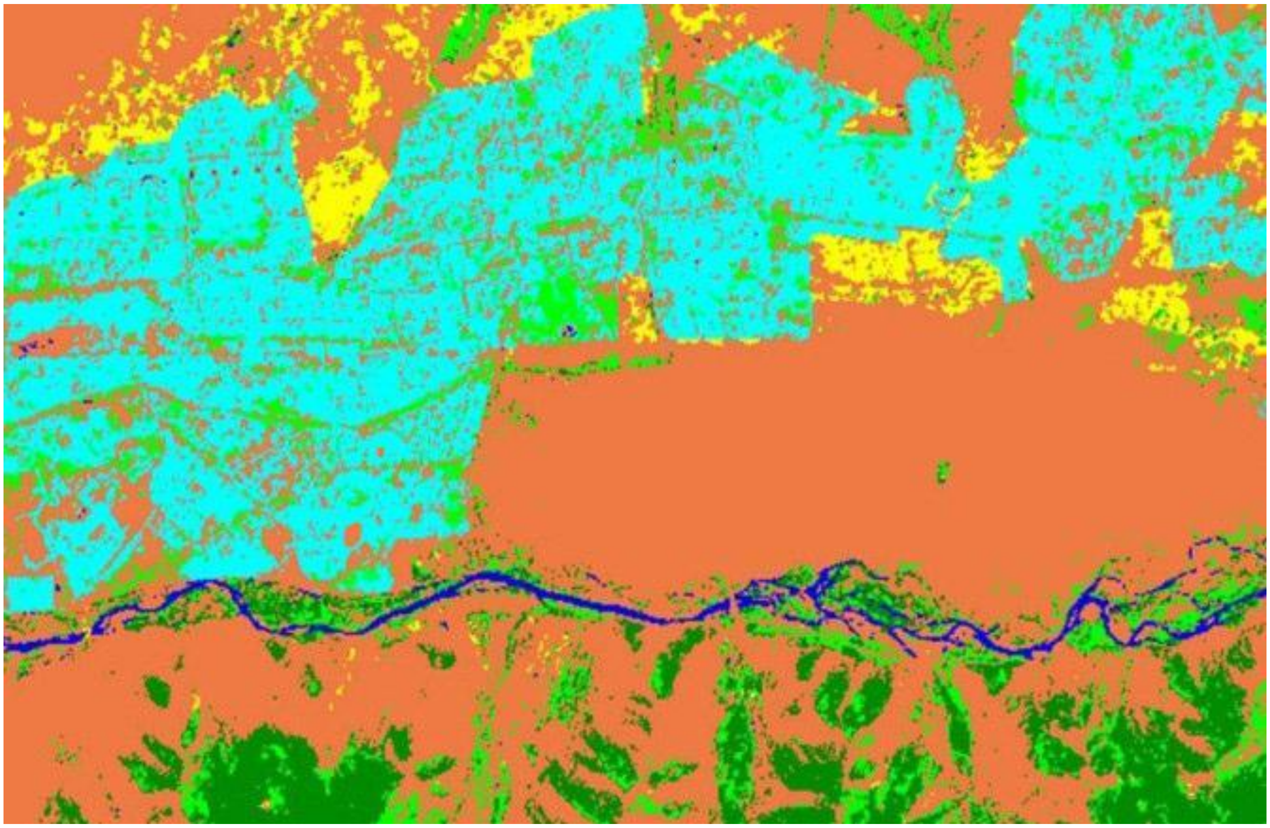

Figure 7. The classification result of the rule-based method (urban area-cyan, ger area-yellow, forest-dark green, vegetation-green, soil-brown, water-blue).

Table 3. The areas for each class evaluated from the rule-based method.

Classes	Total areas in hectares
Building area	2277.83
Ger area	272.23
Forest	709.25
Vegetation	542.36
Soil	4356.28
Water	97.27

satellite images with different spatial and spectral resolutions were used. Overall, the research indicated that the high and very high resolution satellite images can be successfully used for general and detailed urban studies and the proposed methods can be efficiently used for the extraction of accurate thematic information.

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