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Mapping the human settlement of South East Asian cities using ALOS AVNIR-2

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Abstract

Human settlement mapping is essential for socio-economic and urban planning, disaster management and emergency preparation and for other humanitarian support. Effective disaster preparedness requires quantitative spatial distribution patterns of the population in order to position emergency response centers and prepare food and shelter for post disaster management. Mapping human settlements from remote sensing data is cost effective and time efficient, which is suitable for South East Asian countries. This study reports human settlement area mapping of Yangon and Hanoi, using an Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) sensor from Advanced Land Observing and Satellite (ALOS).

Key words: ALOS AVNIR-2 image, human settlements, South East Asian cities

1. Introduction

Determining the spatial distribution patterns and density of populated areas is important for major disaster recovery and emergency management efforts. The use of satellite images to delineate areas of human settlement is cost and time effective, which is suitable for South East Asian countries. Mapping the human settlements by remote sensing data can range from optical daytime sensors (ALOS, Landsat TM/ETM+, SPOT, IKONOS, QuickBird, etc) to nighttime sensors (Defense Meteorological Satellite Program DMSP Operational Linescan System OLS). Moreover, population count is a key factor for much of the official statistical systems and the benchmark for many commercial and research surveys and analyses (Cook, 2004). GIS plays a critical role in population studies and analyses by means of mapping the spatial extent and analyzing it along with other GIS datasets. However, mapping the population is not an easy task due to the nature of human activities which change over space and time. Normally, population can be estimated using statistical and spatial (remote sensing and GIS) approaches. For example, nighttime city lights imagery has been shown to demonstrate a reasonable correlation with population (Sutton *et al*., 2001).

Moreover, in most GIS analyses, population data are commonly available in aggregated geographic units derived from the National Census Bureau or local city office in either text or tabular format. All of these datasets are suitable for local and regional scale analysis but not for micro-scale analysis and decision-making processes. Openshaw (1989) identified the following sources of error in GIS: errors in the positioning of objects, errors in the attributes associated with objects, and errors in modeling spatial variation (e.g. by assuming spatial homogeneity between objects). In GIS analysis, population data are commonly assumed as homogeneous space. However, population data exhibit spatial variation, especially in areas with a mix of high- and low-rise buildings, such as urban areas, residential areas patched with unpopulated spaces (paddy fields, parks, playgrounds or government institutions) as in rural areas. Voss *et al*. (1999) noted that most census boundaries do not coincide with the boundaries of geographic features such as land use/land cover, soil type, geological units, and floodplain and watershed boundaries; this is known as "spatial incongruity" and it arises when spatially aggregated data are available for one set of geographic areal units but not the areal units of primary interest.

Spatial incongruity presents a major obstacle to the integration of social and natural science data, and consequently places limitations on interdisciplinary research efforts. This creates errors when trying to establish accurate rates for GIS analyses pertaining to health studies, crime patterns, hazard/risk assessment, land use planning, or environmental impacts, among others, which rely on a smaller unit of analysis than the original zones. Examples of this are the impact buffers that intersect the census enumeration unit (e.g. overlaying data from units with non-coincident boundaries and/or overlapping spatial units such as census tracts and police precincts or health districts) (Maantay *et al*., 2007).

From a cartographical point of view, a fine-scale dasymetric map can be generated from Land Use/Land Cover LULC, which is commonly derived from remote sensing data. Cartographers use dasymetric mapping for population density over other methods because of its ability to realistically place data over geography. For example,

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Sleeter (2004) produced a medium-scale dasymetric map from land use/land cover maps. Lwin and Murayama (2009, 2010) used building footprints data to estimate the population at building level for micro-scale spatial analysis in order to improve the accuracy in a spatial decision making process.

In this study, we use an ALOS AVNIR-2 sensor, with spatial resolution at 10m and four spectral bands, to delineate the human settlement areas using a multi-spectral classification method by applying a maximum likelihood classifier algorithm. The results were compared with high spatial resolution satellite images (QuickBird at 0.67m spatial resolution). The objective of this study is to delineate the human settlement areas using ALOS-AVNIR2 data for further population estimation and analysis along with other GIS datasets.

2. Study Areas and List of Data

We use ALOS AVNIR-2 satellite images for two South East Asian cities, Yangon (Myanmar), and Hanoi (Vietnam). Table 1 shows the list of data used and purposes of this study. Both cities are quite similar in that they are located on delta regions, composed of low-rise buildings and surrounded by agricultural land.

Table 1 Data, descriptions and applications of their use

ALOS AVNIR-2	
Data Source	ALOS AVNIR-2 Japan Aerospace Exploration Agency (JAXA)
Spectral Bands	Band 1 (Blue: 0.42~0.50 μm) Band 2 (Green: 0.52~0.60 μm) Band 3 (Red: 0.61~0.69 μm) Band 4 (Infrared: 0.76~0.89 μm) 10-m spatial resolution at Nadir
Scenes	Yangon (Myanmar) Hanoi (Vietnam)
Purpose	To delineate the human settlement areas
Google Earth	
Data Source	QuickBird Spatial resolution = 0.67m
Purpose	To validate the ALOS classified image

3. Methodology

In this study, we use a supervised multispectral classification approach which is a procedure for grouping spectrally similar areas on an image by identifying 'training' sites of known targets and then extrapolating those spectral signatures to other areas of unknown targets. Supervised classification relies on the a priori knowledge of the location and identity of the land cover types that are in the image. This can be achieved through field work, study of aerial photographs or other independent sources of information. Various classification schemes have been developed that can be used for remotely sensed data. The major difference between classification schemes is their emphasis and their ability to incorporate remotely sensed information. One of the more common ones was developed by the United States Geological Survey. In this, the Land Use/Land Cover Classification System contains four classification levels and places an emphasis on resources, as opposed to other classification schemes that may be people or activity oriented. Each level of classification is equated with certain data characteristics, such as image resolution.

Some common classification algorithms include: Minimum-distance to the Mean Classifier; Parallelepiped Classifier; and Gaussian Maximum Likelihood Classifier. A Minimum-distance to the Mean Classifier uses the mean values for each of the land cover classes calculated from the training areas. Each pixel within the image is then examined to determine the mean value that it is closest to. Whichever mean value that pixel is closest to, based on Euclidian Distance, is the class to which that pixel will be assigned. The Parallelepiped Classifier uses a mean vector as opposed to a single mean value. The vector contains an upper and lower threshold, which dictates the class to which a pixel will be assigned. If a pixel is above the lower threshold and below the upper threshold, then it is assigned to that class. If the pixel does not lie within the thresholds of any mean vectors, then it is assigned to an unclassified or null category. A Gaussian Maximum Likelihood Classifier evaluates the variance and co-variance of the various classes when determining in the class in which to place an unknown pixel. The statistical probability of a pixel belonging to a class is calculated based on the mean vector and co-variance matrix. A pixel is assigned to the class that contains the highest probability. Once a classification has been conducted, an accuracy assessment must be made to determine how correct the classified image is. An accuracy assessment involves the determination of the overall accuracy of the classification, errors of omission, errors of commission, producer's accuracy, and consumer's accuracy. All measures give an indication of how well the classification of the image was conducted. It is common practice to conduct two or more iterations of a classification process, to improve the accuracy of the result. With each iteration, the test sites are edited to better reflect the representation of their class and to remove or reduce any class overlap (Source: Canada Centre for Remote Sensing CCRS).

We apply a Gaussian Maximum Likelihood Classifier algorithm to perform multispectral classification. The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The likelihood Lk is defined as the posterior probability of a pixel belonging to class k.

Lk = P(k/X) = P(k)*P(X/k) /P(i)*P(X/i)
where

P(k)	prior probability of class k
P(X/k)	conditional probability to observe X from class k, or probability density function

Usually P(k) is assumed to be equal to each other and P(i)*P(X/i) is common to all classes. Therefore Lk depends on P(X/k) or the probability density function. Figure 1 shows the overall work flow used in this study.

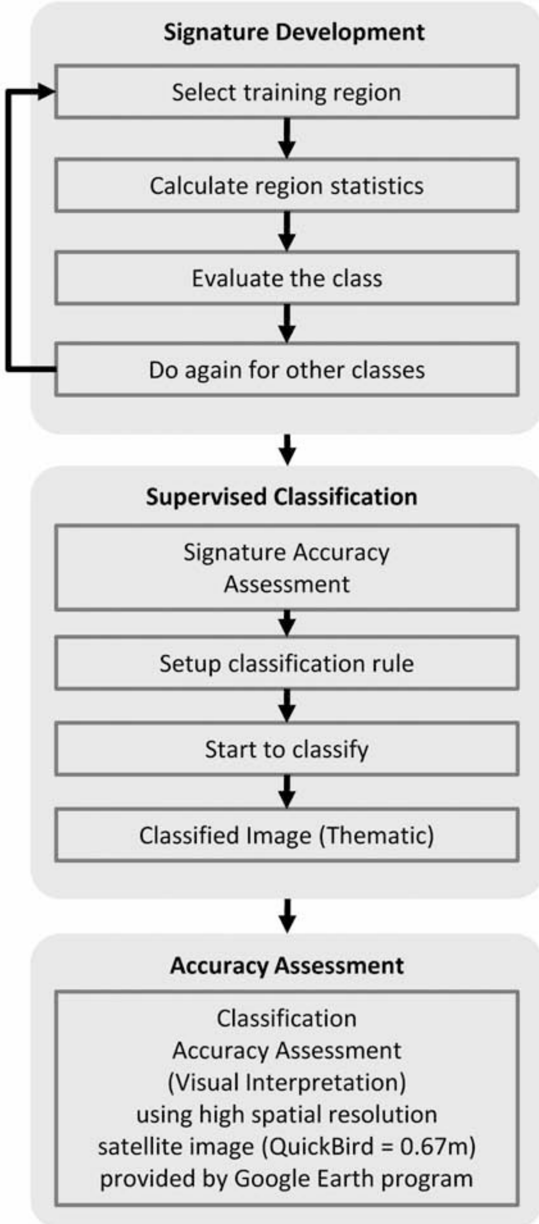

Fig. 1 Overall work flow in this study

4. Results and Discussion

Figures 2 and 3 show the classified images of Yangon City (Myanmar) and Hanoi City (Vietnam). Seven land use classes are identified and named as Urban Dense, Urban Sparse, Grass Land, Forest, Agricultural Land, Barren Land and Water. Urban dense areas are mainly composed of large building structures, highways and other commercial buildings. Urban sparse areas are composed of public housing and commonly patched with grassland and barren land. Agricultural land includes crop and paddy fields. However, the Yangon City image was taken on April 23, 2010, the dry season. Because of this, the paddy fields and other agricultural land have similar spectral values. The Hanoi City image was taken on November 23, 2009, the growing season. In this case, the paddy fields are similar to grasslands. However, the purpose of this classification is to delineate the human settlement areas such as urban dense (downtown) and sparse (rural) areas. The vegetation growing season is useful for the separation of urban and other land use types. Barren lands include small sand-dunes and other dry areas. Water surfaces include both lakes and rivers.

The classified results were validated by high spatial resolution from the Google Earth program. The spatial distribution patterns of human settlement areas are clearly identified in both the cities of Yangon and Hanoi (Figures 2 and 3). Some major roads can be detected (Figure 4) in both cities due to the 10m spatial resolution of the AVNIR-2 sensor. However, this has also introduced some misclassification, such as large cargo ships and small sand-dunes also being classified as urban areas. Building shadows are also misclassified as water (Figure 5).

We also performed an accuracy assessment by generating 120 random points on Google Earth's high-resolution satellite image and recorded actual land use/cover type. These points are later compared with the classified images and Kappa Statistics and accuracy percentage are computed. Table 2 shows the Kappa value and classification accuracy percentage for the Yangon and Hanoi classified images.

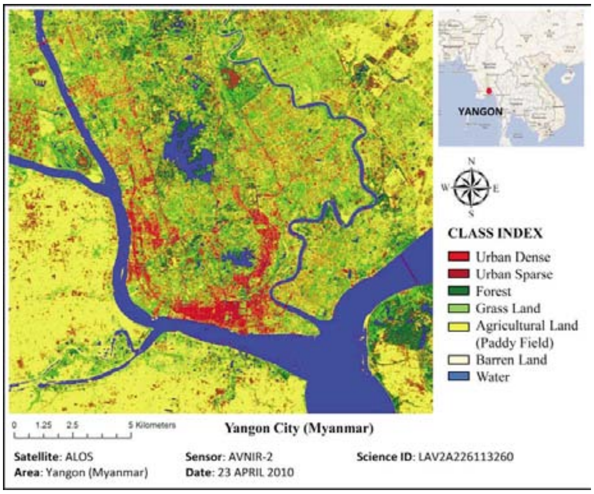

Fig. 2 Multispectral classification of ALOS AVNIR-2 data for Yangon City (Myanmar)

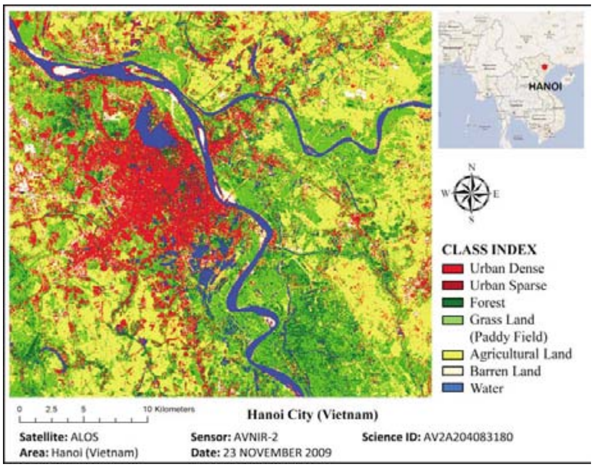

Fig. 3 Multispectral classification of ALOS AVNIR-2 data for Hanoi City (Vietnam)

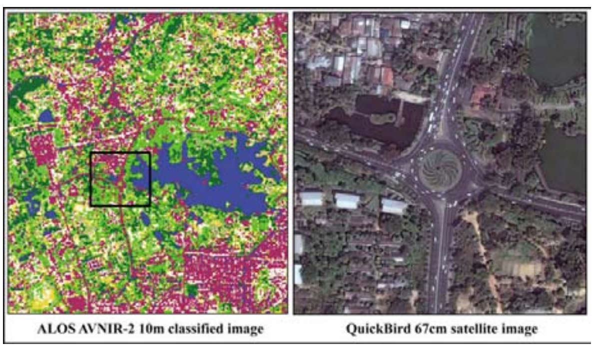

Fig. 4 Validation of ALOS AVNIR-2 classified image with a QuickBird high-resolution satellite image for mixed urban areas (Yangon City, Myanmar)

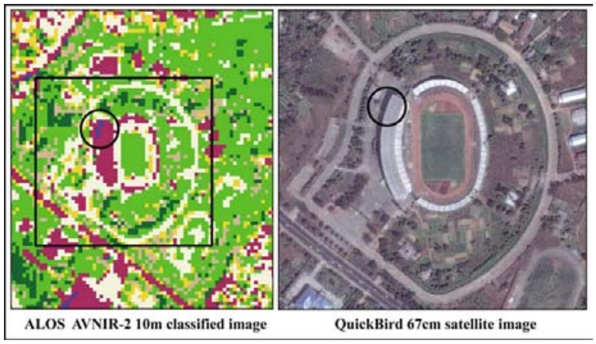

Fig. 5 Misclassified pixels (building shadows are classified as water), Yangon City (Myanmar)

Table 2 Accuracy assessment for both classified images

Yangon classified image	
Overall Kappa Statistics	0.8622
Overall Classification Accuracy	89.84%
Hanoi classified image	
Overall Kappa Statistics	0.8314
Overall Classification Accuracy	86.67%

5. Conclusion

A multispectral classification approach is suitable for medium-resolution satellite images such as Landsat TM/ETM+, SPOT and ALOS, but not suitable for high-resolution satellite images like IKONOS and QuickBird. High-resolution satellite images introduce more detail, such are tree shadows, building shadows and other unnecessary classes. These high-resolution satellite images can be classified as object-oriented classification approaches. In this study, the advantage of ALOS AVNIR-2 for human settlement mapping is favorable due to the clear delineation of urban land use boundaries at a 10m spatial resolution. However, the shadows of high-rise buildings are misclassified as water. Large ships and small-sand dues are also misclassified as urban areas. Generally, ALOS AVNIR-2 data are suitable for areas of low-rise buildings and are good to study vegetation analysis in urban areas. Vegetation areas delineated by the ALOS AVNIR-2 sensor are quite suitable for urban green space identification and eco-friendly walk score calculation (Lwin and Murayama, 2011).

The spatial distribution patterns of human settlements are useful for the estimation of population and disaster management applications. The use of satellite remote sensing data for human settlement mapping is cost and time efficient, which is suitable for quick disaster response and emergency preparedness.

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Canada Centre for Remote Sensing CCRS
http://www.ccrs.nrcan.gc.ca/glossary/index_e.php?id=600

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