

# Urban Building Inventory for Bangkok City with Very High-Resolution Remote Sensing Data

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## 1. Introduction

Bangkok, the capital city of Thailand, is one of the major cities in Asia and a regional hub. The city has a high economic growth and every year many new constructions take place. It is situated on the low flat plain of Chao Phraya River, which extends to the Gulf of Thailand. Floods are the most frequent natural disasters in Bangkok affecting large number of population and causing huge economic damage every year. Although Bangkok is located in low seismic hazard area, there is a potential risk from distant earthquakes, due to the ability of underlying soft clay, to amplify ground motions (Warnitchai et al., 2000).

Disaster risk analysis is important not only to estimate the losses from future events but also to make recommendations for prevention, preparedness and response. Building inventories are essential for all types of disaster risk analysis models. With a slight difference in characterization of building types, all models require an estimate of number of buildings or total square footage (Eguchi et al., 2000). Land use information is very important for disaster risk analysis in urban areas. Traditional land surveying methods, such as field surveys, aerial photography, etc. are costly and time consuming. There is no single reliable source, which can be used for developing a unique database for building and infrastructures located in an urban area. Padermkul (1999) developed an inventory methodology for Bangkok metropolitan area using multiple data sources. However, these sources contain old data and are not updated regularly. The data have been recorded for some specific period and for other periods are not available. Some of the sources keep data only for some specific categories of buildings. Another problem is with the building type classification system. Such as, the building classification system of the Department of Public Works does not match with that of the Department of Policy and Planning. Padermkul (1999) used interpolation and extrapolation techniques to find the missing data, which does not reflect the actual feature of the region.

In order to rapidly derive detailed land use information in broad areas, it is necessary to use remote sensing techniques. Within these few years fine spatial resolution satellite imagery has become widely available. Such as the QuickBird satellite and several new satellite sensors being developed are capable of generating imagery with spatial resolutions as fine as 0.6m in panchromatic mode and 2.8m in multi spectral mode. Many details such as buildings, roads, and other component elements of urban structures can be clearly identified from these high-resolution satellite images and this has opened a new window for urban land use information studies. A few studies, in the past years, were done to use satellite imagery to develop building and other infrastructures inventories for urban areas. Yamazaki et al. (2000) investigated the capability of developing building inventory used for seismic risk analysis using satellite images from LANDSAT, IRS, JERS-1, ADEOS and IKONOS. They used principal component analysis and found this method as a possible solution to classify urban structures. However, Sande et al. (2003) proposed a segmentation and classification approach for IKONOS-2 imagery for land cover mapping to assist flood risk and damage assessment using object oriented image analysis technique.

Purpose of this research was to develop an up-to-date building inventory using information obtained from remote sensing data analysis and existing databases. The main objectives were as follows:

- Analysis of very high-resolution satellite remote sensing data for deriving urban building features.
- Development of an inventory for buildings for an urban area for disaster risk analysis.

## 2. Study Area

The study site selected is a part of the Bangkok Metropolitan Area (Figure 1). The area, measured about 52 km<sup>2</sup>, comprises of mainly residential areas along with a few industrial sites. Most of the buildings are single housing type. The common practice of building houses in the selected area is with concrete moment resisting frame with in filled non-reinforced masonry walls.

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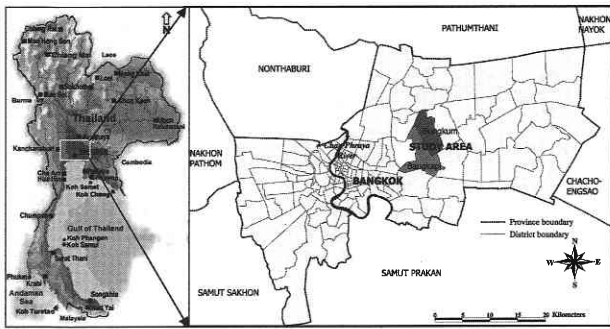


Figure 1 Location of the Study area

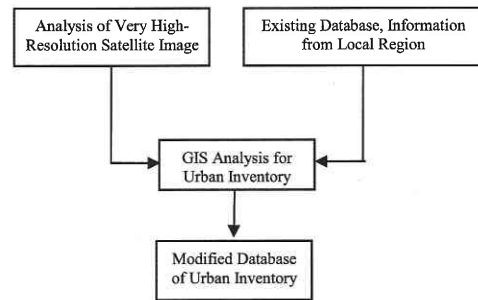


Figure 2 Overall inventory methodology

Reinforced concrete roofs, concrete tiled roofs, and metal roofing's are very common in the selected study area. However, details about the individual buildings were not found from any existing database. The roads are found as cement concrete roads with foot over bridges at regular intervals. The roads are separated with wide road dividers and at road intersections flyovers exist.

### 3. Methodology

The overall approach adopted for development of an up-to-date building inventory is shown in Figure 2. The existing building database is supplemented with the outcomes of the image analysis of very high resolution remote sensing data for the study area. A GIS platform was utilized to integrate the extracted information from image analysis and existing information of the region.

#### 3.1 Image Analysis

QuickBird (panchromatic and multi-spectral) images were used in this study, for development of urban building inventory. Specification of QuickBird image is shown in Table 1. The main objective of this study is to obtain information on buildings and other important structures located in the region. An object oriented image analysis technique was applied in this study. Image segmentation was done using multi-resolution image segmentation (eCognition, 2002). The basic elements of an object-oriented approach are image objects. Image objects are contiguous regions in an image. Segmentation is the subdivision of an image into separated regions. Image segmentation is based on a threshold value that is a fusion of both spectral and shape heterogeneity as given by Equation 1 (Benz et al., 2004).

$$f = w_{color} \cdot \Delta h_{color} + w_{shape} \cdot \Delta h_{shape}$$

$$w_{color} \in [0,1], \quad w_{shape} \in [0,1] \quad w_{color} + w_{shape} = 1 \dots \dots \dots (1)$$

Where,

- $w_{color}$  = Relative weight of color
- $w_{shape}$  = Relative weight of shape
- $\Delta h_{color}$  &  $\Delta h_{shape}$  = color and shape heterogeneity

Table 1 Specification of QuickBird image used in this study

Acquisition date	11/07/2002
Spatial resolution	2.80 m multi-spectral bands 0.60 m panchromatic
Spectral wavebands	0.45-0.52 m (Blue) 0.52-0.60 m (Green) 0.63-0.69 m (Red) 0.76-0.90 m (Near IR)
Map projection	UTM
View angle	Nadir
Swath width	16.5 km

Fuzzy classification technique is image segment classification. It is a very powerful soft classifier besides neural networks and probabilistic approaches (Curlander and Kober, 1992; Benz et al., 2004). As an expert system (Tsatsoulis, 1993) for classification it takes into account the followings (Benz et al., 2004):

- Uncertainty in sensor measurements
- Parameter variations due to limited sensor calibration
- Vague class descriptions
- Class mixtures due to limited resolution

Fuzzy classification consists of an n-dimensional tuple of membership degrees, which describes the degrees of class assignment  $\mu$  of the considered object (*obj*) to the *n* considered classes (Equation 2).

$$f_{class,obj} = [\mu_{class_1}(obj), \mu_{class_2}(obj), \mu_{class_3}(obj) \dots \mu_{class_n}(obj)] \dots \dots \dots (2)$$

Four different levels were chosen to extract features of interest from different levels. Table 2 shows the segmentation parameters used as relative values and as a function of thematic land cover. As shown in the Table 2 and Figure 3, the spectral bands can either be included or excluded from the segmentation process. The scale parameter was the most important factor to control the size of the objects.

The classification was done on the image objects using multi

Table 2 Image segmentation parameters used for segmentation of QuickBird

Segmentation & classification level	Land use types	QuickBird bands used				Scale	Homogeneity criterion			
		Blue	Green	Red	NIR		Color	Shape	Shape settings	
									Smoothness	Compactness
Level 1	All	Yes	Yes	Yes	Yes	5	0.7	0.3	0.9	0.1
Level 2	Buildings & Roads	No	Yes	Yes	Yes	10	0.5	0.5	0.9	0.1
Level 3	Major Roads	No	Yes	Yes	Yes	25	0.5	0.5	0.9	0.1
Level 4	Large Water bodies	No	No	Yes	Yes	40	0.9	0.1	0.9	0.1

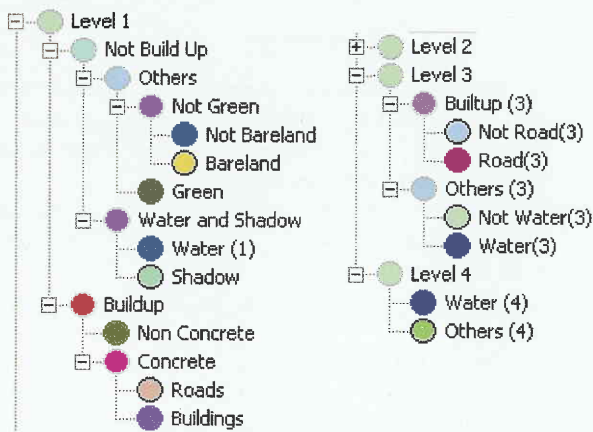


Figure 3: (a) Class Hierarchy with detailed classes of Level 1; (b) Class Hierarchy with detailed classes of Level 3 and Level 4 from digitization (% of the total area)

level classification approach based on fuzzy methods. Fuzzy classification technique was applied with the help of membership function. Membership functions were developed based on the spectral reflectance characteristics and shape properties of the image objects. Different features were separated using different membership functions. One-dimensional membership functions were used in this study. To separate different urban features, (e.g., concrete surfaces, non-concrete surfaces, green areas, bareland, water bodies, etc) spectral information based on image objects were used. Buildings were separated from roads based on their shape properties. The classified image views are shown in Figure 4.

Field survey was carried out to obtain information about the features and to obtain 'ground truth' data. Field survey data was used as the primary knowledge base and was combined with the spectral information obtained from the image objects to develop membership functions for different classes.

#### 4. Result Analyses

Buildings were extracted from segmentations at levels 1 and 2. Buildings were classified as reinforced and non-reinforced concrete buildings depending on their roofing materials and types. Small roads were extracted from segmentation at level 2 where as large roads were extracted from segmentation at level 3.

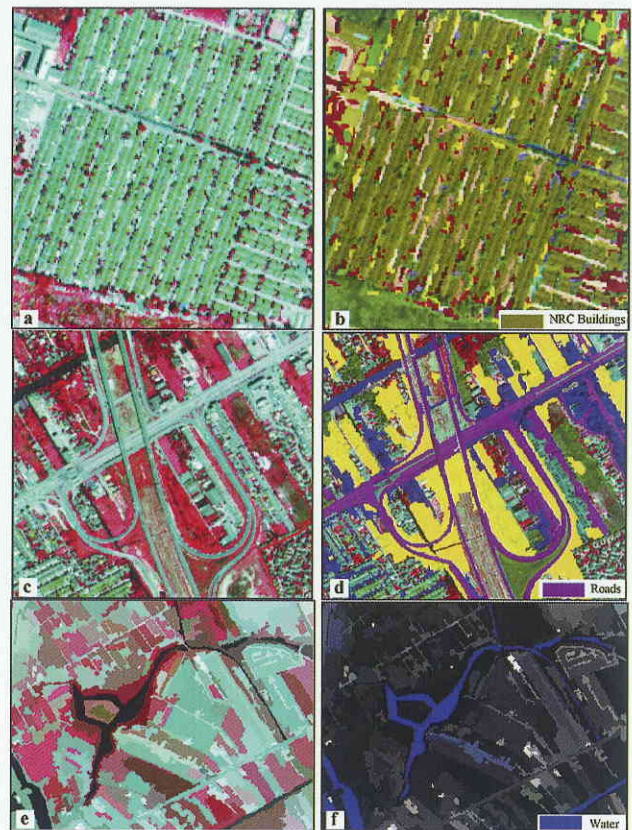


Figure 4. (a), (c), and (e) Image views in false color (432) composite; (b), (d) and (f) Classified image views

Segmentation at level 4 was used to classify the large objects, e.g. large water bodies, in the study area. The classification results are summarized in Table 3. About 38% of the total area was classified as built up area of which approximately 90% was classified as building area. From visual interpretation of the panchromatic image of 60 cm, approximately 36% of the total area was classified as built up area, which is about 95% of the area obtained from image analysis. It was possible to separate shadows from other features, however, 33% shadow objects were classified as water.

#### 4.1 Accuracy Assessment

Two different approaches were applied to verify the classification results. The classification results were verified with ground truth data (Table 4). Image objects were considered to verify the classification system. An overall accuracy of 85% was achieved with the classification scheme. However some of the classes, e.g. RC buildings, green areas and bareland, were classified with high level of accuracy up to 100%. Non RC buildings and roads were classified with accuracy of 70% and 80% respectively. Digitized data of the study area was developed using manual classification with the help of visual interpretation and photographs obtained from field survey. The areas of different features extracted from image analysis were compared with the areas obtained by digitization.

研 究 速 報

Table 3 Features extracted from QuickBird image analysis and from digitization (% of the total area)

Class		QuickBird	Digitized
Built up	Road	3.29	4.24
	RC Building	10.65	11.20
	NRC Building	23.33	20.10
Green		42.79	57.31
Bareland		13.81	
Water		3.20	3.85
Shadow		0.60	3.30
Others		3.33	

Table 4 Error Matrix of QuickBird image Classification

QuickBird Classification	Ground Truth							Total
	RC Building	Road	Non RC Building	Water	Shadow	Green	Bareland	
RC Building	10							10
Road	3	7						10
Non RC Building			7			1	2	10
Water				8				8
Shadow				3	6			9
Green						10		10
Bareland							5	5
Total								62

Overall Accuracy = 54/62 = 0.8548

ing. The comparison of the results obtained from two analyses is shown in Table 3. RC buildings area extracted from image analysis was 95% of the area obtained by digitization. Non RC buildings area was extracted as 116% of the digitized area. Shapes of buildings, roads and water bodies, extracted from image analysis, were overlaid on the shapes obtained from digitization. There was large deviation, in terms of regularity of shape, between two shapes.

5. Concluding Remarks

This study was aimed to develop an inventory for buildings located in the urban areas using remotely sensed data. Buildings were classified with approximately 90% accuracy. The shapes of the roads and water bodies were found as regular shapes. However, the regular shapes of the buildings were not found from the image analysis.

From this study, the following conclusions can be drawn:

- QuickBird image can be a very good choice to develop an inventory for urban features. City area consists of small and large buildings and roads along with other structures. Small houses, roads, water bodies and other features are clearly visible and identifiable from QuickBird image.
- With the object-oriented classification scheme used in this study, an overall accuracy of 85% was achieved in detailed

classification of urban landcover in the study area.

- From this study, it is found that many urban features completely or partly covered with trees and shadows. From analysis of QuickBird image it was found that 0.6% of the total land area was covered by shadow. Using remote sensing data, it is difficult to extract accurately the features covered with trees or vegetal cover.

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