Impervious Surface Detection in Semi-Urban Environment Using Lidar Data and High Resolution Aerial Photographs

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KEYWORDS

Land use, land cover, impervious surface, semi-urban, object oriented classification, Australia

ABSTRACT

Land use information plays a vital role in effective management of natural resources in any country. It helps manage water, soil, nutrients and plants, animals and provides relationships between land use dynamics, economics and social conditions both in urban and rural areas. The land use and land cover mapping is always a dynamic issue in every country because of the dynamic nature of the land use. Knowledge of land use change patterns has important implications in sustainable development and sustainable environmental management. Impervious surfaces are generally defined as any anthropogenic materials that water cannot infiltrate. Increase in impervious land in urban area is causing high accumulation of storm water during the wet season and causing widespread flooding. This research develops an improved method for impervious land use detection using object–oriented classification system. Although pixel-based approaches have certain strong merits and remain in widespread use, operating at the spatial scale of the pixel can have major drawbacks. Foremost among these is that a pixel's spatial extent may not match the extent of the land cover feature of interest. That is pixel's spatial extent may not match the extent of the land cover feature of interest-the problem of mixed pixels may lead to misclassification. Also, when object of interest is considerably larger than the pixel size such as VHR images, urban area comparisons show that the object oriented approach is superior to pixel based approach in terms of accuracy. Object Oriented classification technique is used to separate urban and non-urban features. Negative values of NDVI helped to classify impervious area. Non elevated impervious surfaces are well addressed by NDVI threshold. LiDAR data is used to separate elevated impervious area. By and large, the research shows that impervious land in urban area can be detected using the developed technique with satisfactory accuracy

1. Introduction

1.1 Background

Land uses changes impact on the natural resources and environment of Australia and result in issues such as soil salinity, acidification, rates of erosion, carbon losses and nutrient and water quality decline pose serious threats to land productivity. The provision of land use information is essential for the implementation of effective assessment and management solutions for these problems(Rowland et al. 2002). Impervious surfaces are generally defined as any anthropogenic materials that water cannot infiltrate(Lu et al. 2011). This research work focuses on the land use and land cover, it intends to study different methods of land use classification/ determination and develop an improved method for assessing land use change in semi-urban environments.

Pixel based image classification is a commonly used approach to study land cover/land use. A number of studies of comparison between the pixel based and object oriented methods have been carried out ((Bhaskaran et al. 2010; Cu et al. 2009; Matinfar et al. 2007; Oruc et al. 2004; Weih & Riggan 2008; Zhou et al. 2009). These comparisons show that the object oriented approach is superior to pixel based approach in terms of accuracy.

1.2 Significance of the Research

This research developed a method to map impervious land use in urban-rural fringe area using High Resolution aerial photograph and LiDAR based on Object-oriented classification method and see the change. Urban growth, changing from green vegetation to man-made infrastructure has different impacts on environment(He et al. 2011). This change especially in urban-rural fringe should be monitored on a regular basis. This study proposes a method to detect land use and its change in semi-urban area.

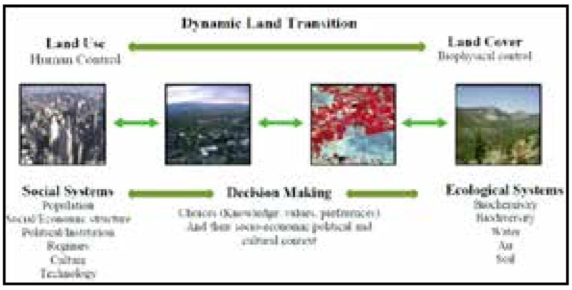

Figure 1-1. Land use-land cover relations(Adapted from Global Plan Report(GLP 2005))

The city of Toowoomba, in the Darling Downs, was hit by flash flooding after more than 160 millimetres (6.3 in) of rain fell in 36 hours to 10 January 2011; this event caused four deaths in a matter of hours. Cars were washed away. Toowoomba sits on the watershed of the Great Dividing Range, some 700 metres (2,300 ft) above sea level.

Figure 1-2. Toowoomba Flood event (Source: Google Search)

The urban impervious area can be estimated to be increased in Toowoomba because of which storms water was quickly accumulated and unexpected inland flood occurred. This research becomes more relevant in this scenario.

Given below are three images of northern part of Toowoomba of three different stages of time 2006(a), 2009(b) 2010(c) which shows the urbanization trend in growing city.

Figure 1-3. Rapid urbanizing area. (Source: Fig. a and b: Google Earth)

2. Use of Object oriented classification

2.1 Object Oriented Classification

Object Oriented Classification, OO, is basically multi resolution segmentation, a patented technique for image object extraction. The segmentation can be used to construct a hierarchical network of image objects. The hierarchical structure represents the information of the image data at different resolutions simultaneously. Fine objects are sub-objects of coarser structures (Baatz et al. 2005). OBIA has been applied for many applications like mapping urban features (Bhaskaran et al. 2010), coal fire study (Yan et al. 2006), sea grass spatial structure mapping (Janas et al. 2009), flood risk and flood damage assessment (Vandersande et al. 2003).

2.2 Comparison between OBIA and Pixel based Classification

In Per Pixel Classification a pixel is assigned to a class based on its feature vector, by comparing it to predefined clusters in the feature space which requires definition of the clusters and methods for comparison. Object Oriented Classification is generally multi resolution segmentation and it can be used to construct a hierarchical network of image objects. Fine objects are sub-objects of coarser structures. Pixel's spatial extent may not match the extent of the land cover feature of interest-the problem of mixed pixels may lead to misclassification
(Blaschke 2010).

Lu et. al. (2011) developed a method based on combination of per-pixel based impervious surface mapping with filtering and unsupervised classification and sub-pixel based method with linear spectral mixture analysis (LSMA). According to Lu et. al. although this method can effectively map impervious surface distribution with Landsat and QuickBird images it has possibility of improving the accuracy using Object based classes.

Table 1: Comparison of Pixel based and Object oriented classification

Per Pixel Classification	Object Oriented Classification
• Pixel is assigned to a class based on its feature vector, by comparing it to predefined clusters in the feature space • comparing each pixel to predefined clusters, which requires definition of the culsturs and methods for comparison	• multi resolution segmentation • can be used to construct a hierarchical network of image obejcts • fine objects are sub-objects of coarser structures

Although pixel-based approaches have certain strong merits and remain in widespread use, operating at the spatial scale of the pixel can have major drawbacks. Chief among these is that a pixel's spatial extent may not match the extent of the land cover feature of interest. For instance, the problem of mixed pixels is well known, whereby a pixel represents more than a single type of land cover (Fisher 1997), often leading to misclassification. This can be compounded by the effect of the sensor point spread function on the area sampled per pixel. Another common problem, though, and one that is less often considered, is where the object of interest is considerably larger than the pixel size(Carleer et al. 2005). There are many research dedicated to compare pixel based approach and object oriented approach of land cover/ land use classification (Cu et al. 2009;

Matinfar et al. 2007; Watmough et al. 2011; Weih & Riggan 2008; Yan et al. 2006).

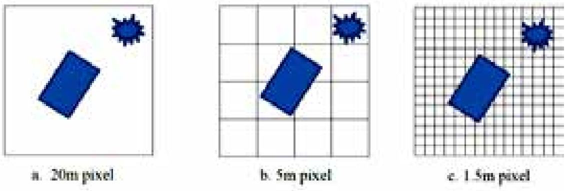

Figure 2-1: Relationship between objects under consideration and spatial resolution(Blaschke 2010)

The figure 2-1 above shows relationship between objects under consideration and spatial resolution: (a) Low resolution: pixels significantly larger than objects, sub-pixel techniques needed. (b) Medium resolution: pixel and objects sizes are of the same order, pixel by- pixel techniques are appropriate. (c) High resolution: pixels are significantly smaller than object; regionalisation of pixels into groups of pixels and finally objects is needed.

3. Method

3.1 Dataset used

High resolution aerial photographs and LiDAR point cloud datasets of Toowoomba, Australia were used for this research. The aerial photograph comprises of 4 bands – band 1,2 and 3 are in visible range and band 4 is infra-red. LiDAR data has an average ground spacing of 0.9 meter.

Figure 2-2: High resolution aerial photograph of project area

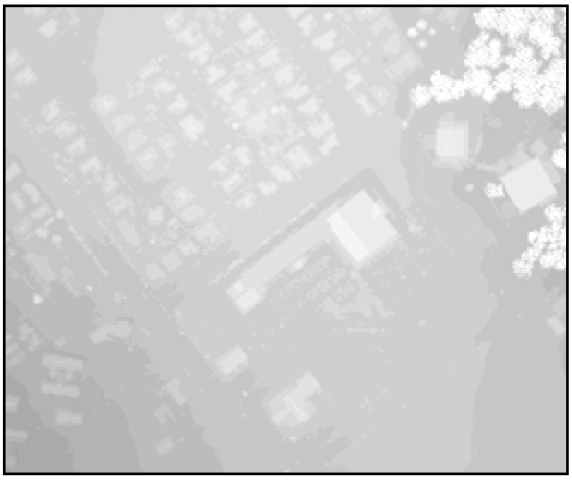

Figure 2-3: Digital Surface Model created from LiDAR point cloud.

Land use classes (ALUM Classification Version 6) developed by ACLUMP are the standard land use classes adopted in Australia. It has a three tired structure – Primary, Secondary and Tertiary. There are six primary classes- Conservation and natural environments, Production from relatively natural environments, Production from dryland agriculture and plantations, Production from irrigated agriculture and plantations, Intensive uses, and Water. Every primary class has different secondary and tertiary landuse classes. Following processes are adopted in the research to classify land use and detect impervious surfaces.

3.2 Date preparation

High resolution Aerial photographs and LiDAR data and other ancillary data are collected from Toowoomba Regional Council, Queensland. Their compatibility is checked. The data structure, suitability of the dataset to use in the research is confirmed.

3.3 Image processing

All the aerial photographs were corrected for radiometry and geometry. Digital Image Processing is largely concerned with four basic operations: image restoration, image enhancement, image classification, image transformation. Image restoration is concerned with the correction and calibration of images in order to achieve as faithful a representation of the earth surface as possible—a fundamental consideration for all applications. Image enhancement is predominantly concerned with the modification of images to optimize their appearance to the visual system. Visual analysis is a key element, even in digital image processing, and the effects of these techniques can be dramatic. Image classification refers to the computer-assisted interpretation of images—an operation that is vital to GIS. Finally, image transformation refers to the derivation of new imagery as a result of some mathematical treatment of the raw image bands.

3.4 LiDAR data processing

LiDAR points cloud is processed to create elevation model. Dilation filer is applied to model the manmade features in a regular and sharp shape. Digital Surface model is created using the first and last returns of the LiDAR data. This gives the impervious building structures and vegetation.

3.5 Image segmentation

The object oriented classification technique constitutes the two processes of object formation (Segmentation) and then labelling the objects thus formed (Classification). Before starting the classification process, segmentation process were done. Image segmentation is the process of completely partitioning an image into non-overlapping segments in the image space (Detwiler et al. 1985)via (Chen et al. 2009)). The resultant segmented objects represent the real world counterparts and are proper in shape. The segmentation algorithm used in eCognition software system is a region-growing method, the main idea of which is to collect the pixels whose attribute values represent a region. A seed pixel is first found as the springboard for region-merging. Neighbouring pixels with attribute values the same as or similar to that of the seed pixel are then consolidated into the region where the seeding pixel lies. The new pixels act as new seeds until no pixel fitting pixels remained. Essential parameters, such as band parting in operation, scale parameter, color criterion, and shape criterion (smoothness and compactness), are set to get ideal segmented results. Among these parameters the scale parameter is the most important factor in determining the size of the objects which decide the maximum allowed heterogeneity for the target image objects(Chen et al. 2009).

eCognition Professional software uses a multi-resolution segmentation approach which is basically a bottom-up approach region-merging technique starting with one-pixel object. In numerous iterative steps, smaller image objects are merged in to bigger ones. The outcome of the segmentation algorithm is controlled by scale and a heterogeneity criterion. The choice of segmentation parameters (scale, colour, smoothness, and compactness) are determined using a systematic trial and error approach and will be validated through visual inspection of quality of the image objects.

3.6 Selection of Algorithm and Image classification

Actual classification will be performed based on the data set and the rules created using a suitable classification algorithm. The actual classification was performed by using the Nearest Neighbour (NN) algorithm as the classifier allows quick and straightforward classification results. Potentially, it can use a variety of variables related to spectral, textural, shape and/or contextual properties of image objects.

3.7 Rule setting for land use classification

Based on the aerial photograph, LiDAR data and other data, different rules were created to assign land use classes to segmented objects. Elevation information, spectral reflection values, existing land use information, land cover information etc. was used to create rules. The classification result achieved through neighbour algorithm was refined by implementation of these rules. The rules were implemented by assigning a membership function. Membership function assigned will be equal to 1(“yes”) if the previously classified image object satisfies the rule condition. Otherwise, the class will receive a membership function value of zero ("No"). All the image objects not satisfying this rule will be assigned the second best class. The figure below explains the method implemented in the research. Normalized Difference Water Index, NDWI, and Normalized Differential Vegetation Index, NDVI were derived from high resolution aerial photograph which also contains infra-red band. The difference of first and last returns of LiDAR points, nDSM (DSM-DTM) will give building, tree, grassland and vacant land. Threshold values (a, b, c) were set for NDWI, NDVI and object height to delineate water (or shadow), vegetation and building structures. Cadastral (Tenure) information, existing land use, elevation information and the land cover objects generated during the classification process were used to implement different rules to find out urban and impervious land use classes. Vegetation and water classes were also extracted during the process although these are not the land use classes intended to classify. The reason of extraction of these classes is to map the changes from vegetation to urban impervious surfaces.

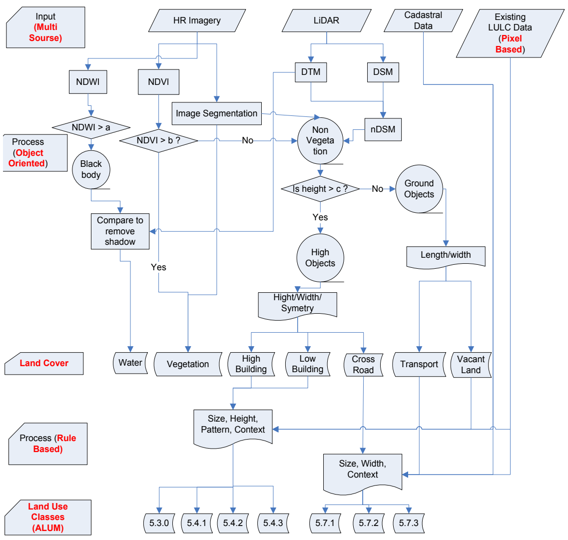

Figure 3-6: Workflow and example rules in OO classification

(5.3.0, 5.4.1, 5.4.2, 5.4.3, 5.7.1, 5.7.2, 5.7.3 are Land use classes in ALUM Classification scheme version 6.0(ACLUMP 2010a)) which come under impervious surfaces)

3.8 Land use class verification

After running the actual classification the primary result of classification are verified on the field and existing land use data to confirm the suitability of the algorithm selected and the rules created.

3.9 Adjustment in the rules and Classification of Images

Based on the result of preliminary land use classification and comparing with the existing land use maps and field verification, necessary adjustment was done in the rules to finalize the classification method.

4. Presentation of Result

Different impervious objects have different spectral characteristics. For example, building roofs with bright or white colour have high reflectance in visible, near-infrared (NIR) and shortwave infrared (SWIR) wavelengths; conversely, roads or building roofs with dark colours can absorb most of the solar energy, resulting in very low surface reflectance in the visible, NIR and SWIR bands. Therefore, bright impervious surfaces appear white, while dark impervious surfaces appear dark grey to black on the IKONOS colour composite image(Lu et al. 2011). The similar theory applies for all of the images in visible optical spectrum. The object oriented classification is presented in the figure below (Figure 4-1). The NDVI could not differentiate blue-painted roofs as impervious class. Elevation information was used to classify blue-painted roofs as impervious class. The part of image below represents different features. It includes concrete parking lot in a shopping mall, roads, driveways etc. Few tree canopies were also classified as impervious class, this is because of shadow of big trees over small ones. Elevation information from LiDAR DSM was used to differentiate between shadow and dark objects.

Figure 4-1: Impervious land use classes shown over aerial photograph (RGB).

The result was found satisfactory. Even small driveways of residential houses were classified as impervious surfaces. Due to unavailability of detailed land use classification map, it could not be compared with the existing land use map. The impervious land-use classes were then further classified according to the land use classes derived by Australian Land Use and Management (ALUM) classification scheme version 6. The classified land use classes were 5.3.0(Manufacturing and industrial), 5.4.x (Urban Residential, Rural Residential, Rural Living), 5.7.x (Transport and communication). The impervious land use classes detected by this method were validated by field visit and local knowledge.

Further research should be in developing methodology to classify all types of land use classes using object oriented classification method.

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