3.1. Introduction

Development of the scientific basis for the relationship between landuse and impervious surface began in the field of urban hydrology during the 1970’s (Barbec et al, 2002). In the early studies, Imperviousness was evaluated in four ways: 1) identifying impervious areas on aerial photography and then measuring them using a planimeter, 2) overlaying a grid on an aerial photograph and counting the number of intersections that overlaid a variety of land uses or impervious features, 3) digital image classification and 4) equating the percentage of urbanization with the percentage of imperviousness.

Many factors must be taken into account in selecting an image processing method for use. A review of the literature on remote sensing of impervious surfaces over the past decade shows that spatial resolution of remotely sensed data is an important consideration in the selection of image
processing methods to be used. Researchers may have to consider the user's need, research objectives, availability of remotely sensed data, compatibility with previous work, and availability of image processing algorithms and computer software, and time constraints (Lu & Weng, 2007). Among these factors, the selection of suitable remote sensing data is the first important step for a successful application (Phinn, 1998; Phinn et al., 2000). The data selection closely relates to research purposes and requirement, the scale and characteristics of a study area, the analyst's understanding of image data and their characteristics, cost and time constraints. Since remotely sensed data vary in spatial, geometric, radiometric, spectral, and temporal resolutions, complete understanding of the strength and weakness of various types of data is key to a proper data selection.

Numerous research efforts have been devoted to quantify urban impervious surfaces using ground-measured and remotely sensed data (Deguchi and Sugio, 1994; Phinn et al., 2000). The methodologies range from multiple regression (Foster, 1980; Ridd, 1995; Xiao et al, 2007), spectral mixture analysis (Lu et al, 2011), artificial neural network (Civico and Hurd, 1997), classification trees (Yang et al, 2003), integration of remote sensing data with geographic information systems (Prisloe et al., 2001) and digital image classification. Various methods of estimation and mapping of impervious surfaces are discussed below.

3.2. Methods of Estimation of Impervious Surfaces

3.2.1. Optical Surveying and Global Positioning Systems

The first method involves the physical measurement and quantification of area for all impervious surfaces by either a traditional optical ground-based survey technique or through the use of a global positioning system (GPS).
3.2.2. Aerial Photography

Similar to optical surveying and GPS, interpretation of aerial photographs can be time consuming and very expensive. Application of aerial photography is only suitable for small area impervious surface mapping.

3.2.3. Population Density

A more indirect approach of estimating impervious surfaces is in using population densities. Stankowski (1972) developed a quantitative index of urban land use characteristics that could then be applied to water resource analyses. From his results, Stankowski suggested population density was the only independent variable needed to empirically estimate proportions of impervious surfaces associated with different degrees of urban development.

3.2.4. Digital Image Classification

Image classification is one of the widely used methods in extraction of impervious surfaces (Hodgson et al., 2003; Dougherty et al., 2004; Jennings et al., 2004), but results are often not satisfactory because of the limitation of spatial resolution in medium resolution imagery, spectral similarity of various features in an image and the heterogeneity of urban landscapes. The ultimate aim of image classification process is to categorize all pixels in a digital image into one of several land use/land cover classes or “themes” (Lillesand and Kiefer, 2000).

Digital classification techniques are of two types: supervised classification and unsupervised classification. In a supervised classification, the analyst identifies in the imagery homogeneous representative samples of the different surface cover types (information classes) of interest. These samples are referred to as training areas. The selection of appropriate training
areas is based on the analyst's familiarity with the geographical area and their knowledge of the actual surface cover types present in the image. Thus, the analyst is "supervising" the categorization of a set of specific classes. The numerical information in all spectral bands for the pixels comprising these areas is used to "train" the computer to recognize spectrally similar areas for each class. The computer uses a special program or algorithm (of which there are several variations), to determine the numerical "signatures" for each training class. Once the computer has determined the signatures for each class, each pixel in the image is compared to these signatures and labelled as the class it most closely "resembles" digitally. Thus, in a supervised classification we are first identifying the information classes which are then used to determine the spectral classes which represent them. There are mainly three classification algorithms: Mean distance to minimum, Parallelopiped and Maximum likelihood classifier (MLC). MLC is the most accurate among these three (Lillesand et al, 2004, P.T.Dipson, 2012). Unsupervised classification image do not utilize training data as the basis of classification. This family of classifiers involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on the natural grouping or clusters present in the image values. A widely used method for unsupervised classification is an algorithm Called Iterative Self Organizing Data Analysis (ISODATA).

3.2.5. Application of NDVI, Tasseled cap greenness and PCA

Because of the near inverse correlation between impervious surface and vegetation cover in urban areas, one potential approach for impervious surface extraction is through information on vegetation distribution (; Carlson & Arthur, 2000; Gillies et al., 2003, Bauer et al., 2007). Normalised Difference Vegetation Index (NDVI) is a numerical indicator that uses the visible and
near infrared region of the electromagnetic spectrum and is used to assess whether the target being observed contains live green vegetation or not. The NDVI subtracts the red reflectance values from the near infrared (NIR) and divides by the sum of NIR and red bands. The NDVI or tasseled cap greenness or principal component analysis (PCA) can be utilized to represent vegetation distribution. Impervious surfaces are then estimated based on: (1) complement of vegetation fraction; or (2) regression models with vegetation indices.

3.2.6. Sub-Pixel Analysis

The area represented by a single pixel in an image may contain more than one thematic class. Such a problem arises due to many reasons and makes it difficult to process the data using conventional classification techniques. In such cases with mixed pixel problem, sub-pixel classification can be implemented. The idealized, pure signatures for a spectral class is called an end member. Because of sensor noise and within class signature variability, end members only exist in concept and as idealizations in real images. There are many different methods of implementing sub-pixel classification. Regression analysis, Spectral mixture analysis, artificial neural networks, soft maximum likelihood classifier, support vector machines etc. can be employed to do sub-pixel classification. However, these methods share a common problem, that is, impervious surface tends to be overestimated in the areas with small amounts of impervious surface, but is underestimated in the areas with large amounts of impervious surface.

3.2.7. Regression Models

Another method is regression, either statistical regression which relates percent ISA to; Tasseled cap’ greenness (Bauer et al, 2004) or regression
Chapter 3

Yang et al. (2003) extended the regression method by developing a classification and regression tree (CART) algorithm, which used the classification result of high resolution imagery as the training dataset to generate a rule-based modeling for prediction of sub-pixel percent imperviousness for a large area.

3.2.8. Artificial Neural Networks

Artificial Neural Network (ANN) has been widely used in remote sensing image analysis. Natural networks can be employed to perform traditional image classification tasks (Civco, 1993; Foody et al., 1995) as well as subpixel classification (Flanagan & Civco, 2001; Lee & Lathrop, 2006). A neural network consists of a set of three or more layers, each made up of multiple nodes. These nodes are somewhat analogous to the neurons in biological network’s layers and include an input layer, an output layer, and one or more hidden layers. The nodes in the input layer represent spectral bands from a remotely sensed image, used as input to the neural network. The nodes in the output layer represent the range of possible output categories to be produced by the network. If the network is being used for image classification, there will be one output node for each classification system.

3.2.9. Object Based Image Analysis (OBIA)

Object based image analysis (OBIA) has been increasingly used in remote sensing applications after the introduction of high resolution satellite imagery, hyper spectral imagery and the emergence of commercial software (Wang et al., 2004). Traditional pixel based approaches have difficulties processing high-resolution imagery resulting in a 'salt-and-pepper' effect where pixels cannot be aggregated properly which later results in poor readability. Classical pixel based techniques assume individual pixels on each
image as independent and they are treated in the classification algorithm without considering any spatial association with neighbouring pixels. ‘Object based’ classifier first segments an image into clusters of similar ‘neighbouring pixels (objects), and then classifies the clusters according to average spatial properties.

3.2.10. Conceptual Models

Ridd (1995) proposed a conceptual model, i.e., vegetation-impervious surface soil (VIS) for urban ecosystem analysis. This framework presents a systematic standard for characterizing urban ecosystem from morphological, biophysical, and anthropogenic perspectives. In this conceptual model, combinations of green vegetation, impervious surface material, and exposed soil were considered the most fundamental components of the urban ecosystem. Using this model detailed land cover land use and biophysical parameters were obtained for urban ecosystems using remote sensing. Wu et al, 2005 applied V-I-S model to Shanghai City, China.As described above numerous methods are there for the estimation of impervious surfaces.

3.3. Data used for the Study

IRS LISS (Linear Imaging Self Scanning Sensor)images for the years 2007, 2009 and 2011 were procured with minimum cloud cover with the help of National Remote Sensing Center (NRSC) image browsing facility. The images for 1990, 1998 and 2014 were downloaded from Global Land Cover Facility (GLCF) and 1973 image was downloaded from U.S. Geological Survey (USGS). The details of the data used are given in the table 3.1.
<table>
<thead>
<tr>
<th>Space-craft</th>
<th>Acquisition Dates</th>
<th>Sensor</th>
<th>Bands</th>
<th>Spatial Resolution (Meter)</th>
<th>Radiometric Resolution (Bits)</th>
<th>Source</th>
<th>Image Details</th>
<th>Level of Processing</th>
</tr>
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<tr>
<td>Landsat-8</td>
<td>11-02-2014</td>
<td>ALI</td>
<td>2,3,4</td>
<td>30</td>
<td>16</td>
<td>GLCF</td>
<td>Path-143, row-53</td>
<td>Geo rectified, radiometric corrected.</td>
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<td>IRS-P6</td>
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<td>LISS-IV</td>
<td>2,3,4</td>
<td>5.6</td>
<td>16</td>
<td>NRSC</td>
<td>Path 99, Row-46, Sub scene-B)</td>
<td>Geo-rectified, radiometric corrected.</td>
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<tr>
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<td>LISS-III</td>
<td>2,3,4</td>
<td>24</td>
<td>7</td>
<td>NRSC</td>
<td>Path-95, Row-66 (70% Shifted to Row 67)</td>
<td>Radiometric corrected</td>
</tr>
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<td>IRS-P6</td>
<td>20-12-2009</td>
<td>LISS-III</td>
<td>2,3,4</td>
<td>24</td>
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<td>NRSC</td>
<td>Path-95, Row-66 (70% Shifted to Row 67)</td>
<td>Geo-Rectified</td>
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<td>IRS-P6</td>
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<td>LISS-III</td>
<td>2,3,4</td>
<td>24</td>
<td>7</td>
<td>NRSC</td>
<td>Path-95, Row-66 (70% Shifted to Row 67)</td>
<td>Radiometric corrected</td>
</tr>
<tr>
<td>IRS-IC</td>
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<td>GLCF</td>
<td>Path-95, Row-66 (70% Shifted to Row 67)</td>
<td>Radiometric corrected</td>
</tr>
<tr>
<td>Landsat 5</td>
<td>24-01-1990</td>
<td>TM</td>
<td>2,3,4</td>
<td>30</td>
<td>8</td>
<td>GLCF</td>
<td>Path-144, Row-53</td>
<td>Geo-Rectified</td>
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<tr>
<td>Landsat 1</td>
<td>10-02-1973</td>
<td>MSS</td>
<td>2,3,4</td>
<td>60</td>
<td>6</td>
<td>USGS</td>
<td>Path-155 Row-53</td>
<td>Radiometric corrected</td>
</tr>
</tbody>
</table>
3.4. Methodology

3.4.1. Pre-processing of Satellite Images

All the LISS III, LISS IV, Landsat MSS and Landsat TM images were co-registered or geometrically corrected using image to image registration with reference to geometrically corrected 2014 Landsat 8 image using first order polynomial equation with nearest neighbour resampling techniques. The Image was projected to UTM WGS 84, zone 43 N projection. All the images were co-registered to < 0.5 pixel accuracy. All the image processing were done in ArcGIS 9.3 and Erdas Imagine 9.1. Digital Number obtained from digital images were first converted to Top of Atmosphere reflectance as mentioned in Chandler and Markholm, 2003. Atmospheric correction was done using minimum pixel subtraction method (Crane, 1971; Chavez et al, 1977, Kok et al, 2009). All the images were georectified and subsetted using the subset tool in data preparation menu in the ERDAS imagine software.

3.4.2. Selection of a suitable method for the preparation of impervious surface map.

Land cover maps having four classes - Water bodies, Vegetation, Open/Exposed and Built-up areas are prepared using three different digital image classification techniques. IRS LISS IV image for the year 2012 having 5.6 m. spatial resolution was used for this analysis, which is having the highest spatial resolution available in public domain. The different classification techniques tried are supervised and unsupervised classifications, as well as Normalised Difference Vegetation Index (NDVI). There are mainly three
classification algorithms for supervised classification. Mean distance to minimum, Mehalanobis distance and Maximum likelihood classifier (MLC) as mentioned in section 3.2.4. Unsupervised classification is done with Iterative Self-organizing Data (ISODATA) Algorithm. In this study, the image is subjected to unsupervised classification with a cluster size of 30 clusters. After classification, each of these 30 clusters is assigned with one of the four land use classes by correlating the classified image with ground reference. After the classification, accuracy assessment to each classified image is done using the accuracy assessment tool in Erdas Imagine. Sampling points (300) were selected at random and the accuracy assessment is done for all the classified images, supported by ground information collected using a Garmin-60 hand held GPS system. Google Earth is also used to obtain the current spatial scenario.

Among all these classification techniques and algorithms ‘Supervised Maximum Likelihood Classification (MLC) yielded the highest classification accuracy and was selected for further estimates. The classification accuracy is in the following order; Supervised MLC > Unsupervised classification > NDVI > Mean distance to minimum > Mehalanobis Distance.
Map 3.1. Land Cover Maps prepared using various Classification Methods
3.4.3. Preparation of ‘Total Impervious Surface (TIA)’ maps

Land cover classified layers for the years 1973, 1990, 1998, 2007, 2009, 2012 and 2014 having the four classes were prepared using supervised MLC classification. Vegetation and Open / Exposed land is considered as pervious and Built-up areas alone is taken as impervious. Confined water bodies, which adds to the perviousness, are absent in the study area. There are only flowing water bodies, which do not add to the infiltration (perviousness) but only increase the run-off. Hence, they are considered neither as pervious nor impervious and hence are left alone as water bodies in Map 3.4. Total Impervious Area (TIA) maps for the city were composed from these layers.

3.4.4. Spatio - Temporal Analysis of Impervious Surfaces

Spatio temporal analysis of TIA is performed by considering the image differences of 1990 and 2014 TIA layers. Even though data for the year 1974 was available, a comparison between 1974 image with 72 m. resolution and 2014 image with 30 m. resolution can result in serious error. Hence only the 1990 image having 30 m. resolution is used for the comparison with 2014 data.

3.5. Results and Discussion

Before 1990, Built-up area in Kochi was quiet low as seen in 1973 image in Map 3.2. Built-up areas can be seen in Mattancherry, Fort-Kochi and Ernakulam area. Kumbalam, Panangad, Palluruthy, Edakochi, Nettoor and Vypin areas seems unoccupied and the island of Vallarpadam is in the formation stage (Locations are shown in Map 2.3). During 1990's, Cochin Port Trust introduced its container storage area near Wellington Island after reclaiming an estuarine area. A major portion of the Wellington Island became occupied (mainly by the Cochin port trust) and Thevara-Wellington Island Bridge was constructed during early 1990's. The industrial activity of
Kochi is concentrated in Eloor and Ambalamugal area. Not only industrial or commercial but also residential areas increased in these areas as can be seen in 1990 image. A tremendous increase in built-up area was seen in M.G road, Kaloor and Ernakulam region. Also the M.G. Road area witnessed the proliferation of several commercial activities, which was later followed by Marine Drive area. After 1998, residential areas spread to Edapally, Edakochi, Kalamassery and Aluva.

![Figure 3.1. Landcover Pattern for 1990-2014](image)

Built-up areas increased tremendously with the construction of NH-47 bypass. The impervious surface expansion mainly takes place along the periphery of new roads as can be seen in Map 3.4. In addition, impervious cover of the city increased considerably with the onset of major developmental activities such as International Container Transshipment Terminal (ICTT), Metro Rail, Liquefied Natural Gas (LNG) Terminal, Kochi International Airport, Smart City, Info Park etc. Construction of ICTT was started in 2005 and it became fully operational in 2011. Metro rail project started in 2013 also added its own share of impervious surface increase for its allied infrastructure developments. Change detection studies shows that impervious cover over the city is increasing at a very rapid pace. Land cover maps for the years 1974, 1990, 1998 and 2007 are given in map 3.2. and that for the years 2009, 2011, 2012 and 2014 are given in the map 3.3. Spatio temporal changes of impervious surface from 1990 to 2014 are given in map 3.4.
3.5.1. Spatio temporal changes of impervious surfaces

Spatio temporal analysis of impervious cover over Kochi shows that along with the increase in urbanization, there is a corresponding decrease in water bodies and vegetation. Analysis of satellite data shows that the impervious coverage of 53.74 km² in 1990 increased to 154.63 km² by 2014, while there was a corresponding decrease of pervious areas from 183.70 km².
to 87.25 km$^2$ during the same period. Also, it can be seen that this change is
not only contributed by conversion of pervious lands into built up area, but
also by land reclamations of the backwaters (map 3.2 and 3.3). This trend was
visible from 1944 to 2009 as shown by Dipson et al (2014). Only, this trend
seems to accelerate in the present decade.

Map.3.4. Total Impervious Area Map
3.6. Conclusion

There are many potential applications for the impervious surface maps prepared from this study. Spatially explicit imperviousness estimates and their trends provide urban planners useful data to assist in their decision making and implementation of management strategies. Applications in this field include urban ecological modelling as well as urban climatological studies. Above all, expansion in impervious surface serves as an indicator of increasing Urban Heat Island (UHI) effect. Geospatial data of impervious surfaces and its change can be used not only as a critical input for urban hydrological modelling but also as an indicator for water quality assessment. Increasing imperviousness plays a big role in degrading water quality and quantity.

This study reveals the rapid increase in impervious coverage concurrent with the development of the Kochi metropolis. This calls forth, the urgent implementation of strict land use policies and planning as well as Best Management Practices for the smooth functioning of the city infrastructure and future city development policies. The frequent disruptions of traffic and other public services after heavy rainfalls have become a part of the city life not only in Kochi, but also in most of the cities in the tropical developing countries. This emphasizes the need to develop planned cities at least in emerging metropolises.

References


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