# **Thesis Proposal: Subpixel impervious surface change detection using Landsat time series**

# **Introduction**

Building a comprehensive understanding of impacts brought by human settlements onto environments and the associated consequences is crucial in studying the pattern and pace of urban expansion. Although urban land only accounts for 3% of Earth’s territorial surface, but it generated enormous negative influences on local ecological system, water and air quality, and agricultural land. Urbanization is also one of the primary drivers of contemporary global land cover change. Therefore, impervious surface cover becomes one of the most important land cover types as more than half of the total population in the world lives in the urban area nowadays (UNFPA, United National Population Fund, 2011). Major impervious surface features include rooftops, sidewalks, and roads, which are all made of artificial materials that water cannot penetrate through. Estimating measurable impervious surface cover for individual cities can provide a theoretical basis for local decision makers to improve urban planning strategies for more efficient management to benefit the environment.

As urban landscape continues to be more heterogeneous, mapping urban expansion remains a complex and challenging task. However, researchers have never stop developing new methods in studying urban growth from local to global spatial scale. Most regional and global studies have been conducted using coarse spatial resolution remote-sensing data sources such as Moderate Resolution Imaging Spectroradiometer (MODIS) (Huang et al., 2016; Deng & Wu, 2013; Schneider et al., 2015; Ma et al., 2014), while medium-to-high resolution satellite images have commonly been utilized for studying urbanization at the scale of individual cities (Song et al., 2016; X. Li et al., 2018). The 2008 free release of long time series Landsat dataset covering broad geographical scale in medium resolution provided great potential for academic researchers to learn the process of urbanization (USGS, 2012). While uncertainties always appear no matter what the data sources are (A Schneider et al., 2015), the best available data sources for mapping accurate individual cities’ urban extents and land use changes is the medium resolution remote-sensing dataset. Therefore, with regard to this study, Landsat medium resolution data made it become possible for mapping multiple-year land cover change maps in HCMC metropolitan area in sub-pixel level and further analyzing information from generated reliable land cover map products.

Moreover, as substantial efforts have been completed in monitoring one stable point of urban expansion with medium-to-high resolution (Zhu et al., 2011; Deng & Wu, 2013), more researchers have started to concentrate on documenting annual urban dynamics as a long-term basis for providing unique record of colossal urbanization processes in the world (Song et al 2016; F. Schug et al 2018; X. Li et al 2018; L. Zhang et al., 2018). Song et al. (2016) established a statistical method for detecting and characterizing the magnitude, timing, and duration of urban expansion based on the resulting dataset from Sexton et al. (2013) with annual stacks of Landsat images between 1986 and 2008. This research has investigated the complex dynamics of urban land-change processes in Washington D.C.–Baltimore metropolitan area at medium spatial resolution and high temporal resolution.

While many areas in North America have had many researches focusing on urban impervious surface cover, it is crucial to meet the needs of updating impervious surface cover information in Southeast Asia which have undergone fast-paced urban transition since 2000. Although numerous cities in the world have declined urban density along with increased urban expansion, the urban densification in Southeast Asia has continued to rise between 2000 and 2010 (A. Schneider et al., 2015). Particularly, Vietnam, with one of the fastest growing economies in the world since 1990 (World Bank, 2017), has continuously expanded its urban areas since the implementation of ‘doi moi’ policy in 1986. After re-engaging into the global economy, Vietnam’s financial center, Ho Chi Minh City, became the most populous city countrywide with continuously increasing human settlement expansion. Within the last 20 decades, the number of city inhabitants of HCMC climbed from approximately 5.27 million to 8.44 million between 2000 and 2017 (General Statistics of Vietnam). By 2030, this city is planned for containing 13 million urban dwellers in total. Additionally, HCMC’s sub-urbanization also spread human settlement as far as 100 km away from its urban core with approximate over 600 km2 cropland converted to built-up land between 1990 and 2012 (Kontgis et al., 2014). Dramatic loss of arable land due to urban growth has severely reduced agricultural production and caused significant environmental consequences, including higher flood frequency and lower biodiversity (Ma et al., 2014).

Although it has been urgent to study the urbanization taking place in HCMC in Vietnam, only a few researches have been completed in studying its urban land cover changes with quantitative methods. Kontgis et al. (2014) monitored peri-urbanization in HCMC with dense temporal stacks of Landsat images between 1990, 2000, 2006, and 2012 using support vector machine (SVM) classifier. Goldblatt et al. (2018) applied Landsat 8 optical images, Sentinel radar data and nighttime light imagery to classify HCMC’s urban area at a per-pixel level in 2000, 2005, 2010, and 2015 with Random Forest classifier. Vu et al. (2018) studied HCMC’s urbanization process in three different high spatial resolutions and conducted both maximum likelihood (ML) and SVM classification. Additionally, Son et al. (2017) extracted impervious surface in HCMC in 1996, 2007, and 2016 with vegetation-impervious-soil (V-I-S) model using Landsat data. As majority of the HCMC articles have focused on creating per-pixel classification maps for stable points of year, characterizing HCMC’s urban land cover at sub-pixel level with a longer temporal scale has remained exceedingly under-explored in the remote sensing field.

Therefore, this study’s main objective was to uncover HCMC metropolitan area’s urban growth between 2000 and 2017 by using dense annual stacks of Landsat images and providing a new method for deriving additional land change information from a set of continuous land-cover maps. This technique exploited spectral information of artificial surfaces and explored the Random Forest machine learning algorithm to handle the heterogeneity of the study area’s urban landscape. We believed that this research would have a promising ability to forecast the future dynamics of land-cover change trends in the HCMC metropolitan area with an advanced method incorporating dense time stacks of Landsat satellite observation data and high-resolution historical reference imagery. All available cloud-contaminated Landsat scenes during rainy season have been obtained even though they were with reduced qualities. Dense time stacks of Landsat highly benefited the change detection of historical urban growth, even though heavy cloud coverage created unequal distribution of data sources (X.Li et al., 2018). By separating the useful built-up feature pixels from the large pixel pool, this study aimed at revealing the specific pattern of land cover conversions related to individual pixel. Also, this approach was believed that it can be applied to a variety of cities with highly heterogeneous nature and ongoing urban development. However, the spectral similarity among urban land, bare land, and undeveloped land in the study area has created great difficulty during our research process. We expected that this unaddressed problem would be solved in the future with new methods successfully isolating land cover types resembling each other.

1. **Literature Review**

There is an extensive number of academic journals investigating urban expansion and land cover changes in different temporal and spatial scales with various methods:

Monitoring peri-urbanization in the greater Ho Chi Minh City Metropolitan Area (Kontgis et al., 2014)

The purpose of this research was to define, characterize, and analyze how peri-urbanization influenced the land cover types and population migration in the greater Ho Chi Minh City metropolitan area. The major concept peri-urbanization occurred between the urban and agricultural areas mostly due to foreign direct investment (FDI). It challenged significantly to agricultural production and affected many local farmers’ livelihoods. The dependent variable was urban expansion. The independent variables were population sizes, cropland acreages, and impervious surface coverages. In the study area, urbanization took place closer to the urban cores between 1990 and 2000, but it became much more unplanned and extended further from the urban core between 2000 and 2012. Also, population grew much faster in the rural and peri-urbanized areas than urban core regions. Overall, a total of 660.2 km2 of cropland in the greater Ho Chi Minh metropolitan area were converted to urbanized areas during the 22-year period. 3.5 million more population and 4.8 more built-up areas were also added into this region.

Classifying and mapping the urban transition in Vietnam (Saksena et al., 2014)

The goal of this paper was to use both national census data of Vietnam and remote sensing satellite images to characterize communes and classify land uses into rural, peri-urban, urban, or urban core to manage rural-to-urban transition in a sustainable way and prevent unequal developments from rapid urban expansion. The dependent variable was urban transition, and the measurable independent variables were fraction of households with income from agriculture, fraction of land under agriculture, fraction of households with modern toilet, and the Normalized Difference Vegetation Index (NDVI). The results designated that peri-urban area has grew up to approximately 7% of Vietnam’s land area and settled about 13% of national population but the governments continued to categorize its peri-urban areas as urban or rural ones. Moreover, vegetation density went down as the percentage of agricultural households decreased and the percentage of households using modern sanitation increased along the rural-urban continuum. Also, the urban classification categorized 3 types of peri-urban communes, including communes on the large towns’ or cities’ edges, communes along highways, and communes in rural areas.

The use of single-date MODIS imagery for estimating large-scale urban impervious surface fraction with spectral mixture analysis and machine learning techniques (Deng & Wu, 2013)

The goal of this paper was to compare and analyze different performance results carried out by spectral mixture analysis (SMA) and two machine learning techniques, including Cubist Regression tree and Random Forests, for mapping large-scale impervious surface fraction. In this paper, coarse-resolution imagery from MODIS with a relatively lower spatial resolution but larger geographic coverage was utilized instead of medium-and-high resolution imagery, such as Landsat TM/ETM+. The researchers selected the states of Virginia and Ohio as their study areas. The independent variable was the impervious surface fraction. The dependent variables for model inputs were eleven spectral indices, including the original reflectance values of seven MODIS bands, Normalized Difference Vegetation Index (NDVI), and three MODIS Tassel Cap components. The comparative analyses suggested that sample set size matters significantly to the selection of methods. Specifically, unconstrained SMA provided a reliable result when the sample sizes were smaller, while Random Forests performed better than Cubist regression tree and kept improving as sample sizes increased.

Mapping sub-pixel urban expansion in China using MODIS and DMSP/OLS nighttime lights (Huang, Schneider & Friedl, 2016)

The objective of this paper was to use coarse-resolution satellite imagery and nighttime lights to map urban extent of nine major metropolitan areas in Eastern, Southern, and Southwestern China, including Beijing, Tianjin, Chengdu, Xi’an, Hangzhou, Ningbo, Kunming, Guangzhou, and Fuzhou, for 2001 and 2010. This research only focused on two types of land cover: urban land and agricultural land. Random Forest Regression model was implemented to predict fractional urban cover due to its well-known ability of dealing with the large size and high complexity of sample data. The independent variable was the fractional urban cover. The dependent variables were nine spectral indices, including seven original MODIS bands, MODIS enhanced vegetation index (EVI), nighttime land surface temperature (LST), and nighttime lights (NTL). The Random Forest models were estimated for both temperate and subtropical regions in China and they show similar performances. The results indicated that EVI was the most important feature for temperate models, while band 7 (shortwave infrared) was the most important one for subtropical models. LST contributed relatively less than the other spectral indices due to the remote sensing data’s coarse spatial resolution. Compared with census-based estimates, MODIS maps show substantially higher built-up land cover percentage. The overestimation of urban land in the MODIS-predicted results was due to the blooming effects of NTL data and coarse spatial resolution of MODIS imagery.

1. **Conceptualization of the Research Problem**

One major concept is urbanization, referring to a territorial and socio-economic progress taking place between urban cover and rural land. Another major concept is land cover changes, as land covers tend to change corresponding to built-up construction resulting from urbanization. The independent variable is impervious surface percentage, which means the proportion of impervious surface cover within one pixel. The dependent variables are Landsat spectral values, which are also the input of the random forest model.

1. **Hypothesis**:

In this research, one null hypothesis and one alternative hypothesis will be tested. Both hypotheses were drawn from extensive literature review about urban expansion and land cover changes:

Null Hypothesis (Ho): There is no relationship between impervious surface percentage and Landsat spectral values.

Alternative Hypothesis (Ha): There is a relationship between impervious surface percentage and Landsat spectral values.

1. **Methodology**

The methodology has three components, including data acquisition, data portrayal, and data analysis.

5.1 Data Acquisition

To perform Random Forests model, time series Landsat TM, ETM+, and OLI surface reflectance images will be employed to estimate impervious surfaces in Ho Chi Minh City. Started from January 2008, USGS and NASA implemented a new data distribution policy that provides Landsat data for free. Therefore, all Landsat data will be collected from United States Geologic Survey Landsat data archive without any costs. Although the issue of haze and cloud cover during rainy seasons in Ho Chi Minh City will greatly limit the use of optical images in land use/cover studies, high resolution satellite images from Google Earth Pro will serve as a highly useful supplement information in sampling generation. This software has been utilized by geography professional from all over the world for acquiring high spatial resolution satellite images.

## 5.2 Data Portrayal

Various tables, figures, and maps will be used to visualize and simplify data in a more understandable form. To begin with, all Landsat images and other data sources will be organized into a data acquisition table. After accomplishing the sub-classification of urban land covers in Ho Chi Minh City, a resulting map of the categorized land uses will be mapped for the time range 2001-2016. Ultimately, for each land cover type, an isoline plot of the mean absolute error and systematic will be created to visualize the accuracy of the results.

5.3 Data Analysis:

The methodology is composed of four steps, including data preprocessing, training/testing sampling, sub-pixel classification, and accuracy assessments. For the first step of data preprocessing, all the satellite images were corrected atmospherically with calibration tool before being downloaded. Universal Transverse Mercator grid system (UTM) – Zone 48 and World Geodetic System 1984 (WGS84) ellipsoid and datum will be selected as the projected coordinate system. After preprocessing Landsat data, both training and testing sample sets will be generated for 2001, 2004, 2007, 2010, 2013, and 2016 from visually interpreting high spatial resolution images on Google Earth. Training samples will guide the classification of image, whereas testing samples will estimate the accuracy of the results (MacLean et al., 2013). Overall, 300 training samples and 300 testing samples will be drawn carefully with satellite image interpreters’ academic knowledge and experiences. Afterwards, the sub-pixel classification method will be performed based on those samples.

Different from the traditional classification method, which assigns each pixel to one single type land cover based on its highest probability, sub-pixel classification categorizes one individual pixel to several classes simultaneously. The satellite imagery utilized for extraction of impervious surface area can be sorted into three types, which are high spatial resolution (such as QuickBird or IKONOS), medium spatial resolution (such as Landsat), and coarse spatial resolution (such as MODIS). Pixels in Ho Chi Minh City area will typically contain a mix of land uses and the possibility for this is even greater with medium or coarse resolution data. Therefore, traditional per-pixel classification analysis will either significantly underestimate or overestimate the impervious surface area.

To avoid this problem, sub-pixel classification approach has been implemented in many studies. This method will identify the areal proportion of classes in each pixel instead of categorizing a whole pixel to only one land cover based on its maximum likelihood. Today, Sub-pixel classification has been applied to remote sensing field using regression models, spectral mixture analysis, and machine learning algorithms. The main idea of regression models is to relate remote sensing or GIS variables to percent impervious surface area in regression analysis for large-scale impervious surface estimation. Bauer et al. related Landsat TM Tassel Cap greenness to actual impervious surface area in regression model analysis and estimated the percent impervious surface area across Twin Cities Metropolitan Area (TCMA), Minnesota, in 1986, 1991, 1998 and 2000 (Bauer et al., 2004).

Furthermore, Random Forest machine learning technique, which have been well-documented for its reliability and efficiency, will be applied into this research to perform sub-pixel classification. Deng and Wu (Deng & Wu, 2013) found that Random Forests could provide more satisfactory estimation results of percent imperviousness in highly heterogeneous study areas, compared to other classic machine learning methods. Specifically, Random Forests is an ensemble learning algorithm that grows many classification trees for improving accuracy of prediction. Each time to classify a new object, the model puts the input vector down each of the trees in the forest. After each tree generates a classification result (or we can say each tree has one vote), the forests choose the classification having the most votes (Fig.2). Moreover, Random Forests does not overfit so that one can run as many classification trees as they want. This model is comprised of 4 principal steps: 1) randomly selecting samples with bootstrap method from the original training sample set; 2) randomly selecting a set of independent variables from all variables; 3) Growing several classification trees without pruning by repeating step 1 and 2; 4) Selecting the finest results for the final prediction based on the votes (Deng & Wu, 2013).

Specifically, for the second step of the Random Forest model, spectral analysis will be performed. No spectral index but all seven original Landsat bands, including Blue, Green, Red, Near Infrared (NIR), Shortwave Infrared (SWIR) 1, Thermal, and Shortwave Infrared (SWIR) 2 will be used to measure land cover changes. Spectral analysis believes that different land covers in a pixel can be represented by a mixed spectrum and that the shares of spectral feature indicate the proportion of land covers in the pixel (Narumasa et al., 2016). Different bands are good at detecting distinct types of land uses. For example, the most important bands for imperviousness prediction were red band, Near Infrared band, and Short Wave Infrared bands.

The last step of the methodology is to estimate the accuracy of the classified results. Two accuracy measurements will be utilized, including mean absolute error (MAE) and systematic error (SE). MAE is used to measure how close the classifers’ predictions are to the eventual outcomes. The smaller the MAE is, the more accurate the results will be. Systematic error will possibly occur when there is something wrong with the data handling system or the uses of instruments. Both errors will be calculated as follows (Deng & Wu, 2013):

## (1)

## (2)

## (3)

where is the predicted urban impervious surface cover percentage for pixel using the Random Forest model; is the ground truth urban impervious surface cover percentage of pixel ; is the total number of the testing samples.

1. **Study Area**

With approximately 8.15 million (2015) in total population and 2095.5 km2 in coverage (2015), Ho Chi Minh is the economic center in Southern Vietnam and the largest city nationwide. Its urban area is consisted of 19 districts and countries, while its rural area contains 98 communes dividing into 5 subdistricts (Nguyen et al., 2016). In general, Ho Chi Minh City can be separated into three parts, which are the urban core, expanded urban area, and rural area. First, the urban core contains districts 1, 3, 4, 5, 6, 8, 10, 11, Binh Thanh, Phu Nhuan, Go Vap, Tan Binh, and Tan Phu. Districts 1, 3, 5, and 6 were consisted of the original Ho Chi Minh City. Areas outside of the innermost area were districts 4, 8, 10, 11, Binh Thanh, and Phu Nhuan. Outermost areas in the urban core were districts Go Vap, Tan Binh, and Tan Phu districts. The expanded urban area included districts 2, 7, 9, 12, Thu Duc, and Binh Tan. Rural area contained Hoc Mon, Binh Chanh, Nha Be, Cu Chi, and Can Gio districts. In particular, Cu Chi and Can Gio districts were located at the outermost areas of Ho Chi Minh City (Fig.3).

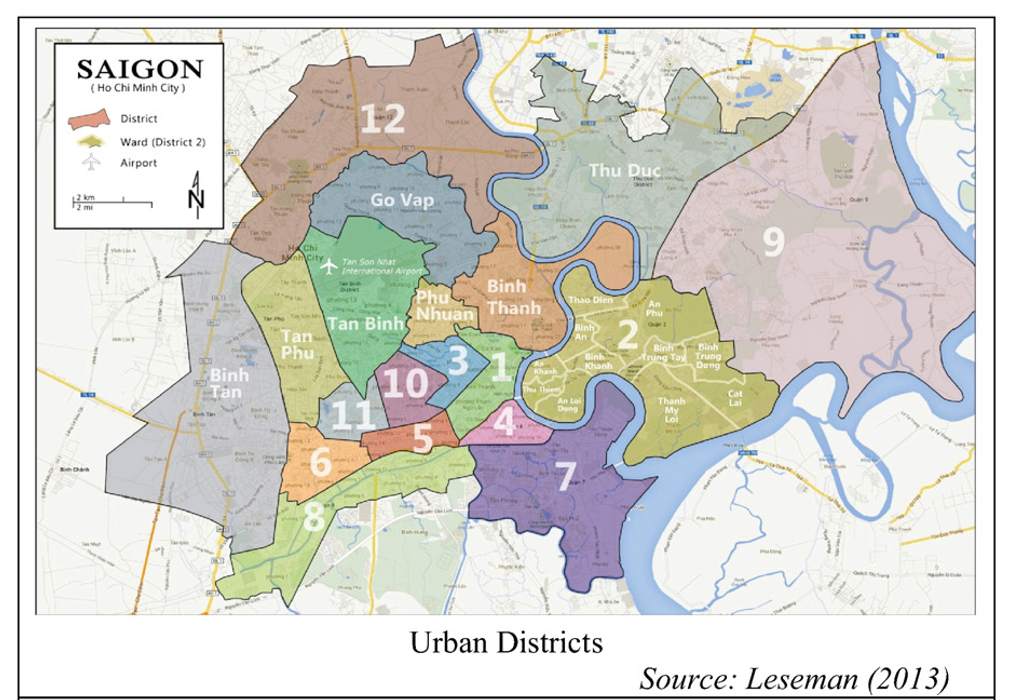


Figure. 1. Study Area – Ho Chi Minh City

Furthermore, Ho Chi Minh City is also a fast-emerging Asian coastal megacity in the global world due to its massive population growth and urban expansion. From 1997 to 2003, 6 new urban districts were formed in Ho Chi Minh City. Due to massive urban transition from rural to urban, the urban area in this city increased 351.85 km2 by 2008. The total population in Ho Chi Minh City has increased from around 5.45 million to 8.15 million from 2001 to 2015 (General Statistics Office of Vietnam). The urban population in Ho Chi Minh City has increased from approximately 4.48 million in 2001 to 6.68 million in 2015, while the rural population also increased from 0.98 million to 1.46 million (General Statistics Office of Vietnam). It is expected that the total population in Ho Chi Minh City Metropolitan area will reach 11.6 million 2025.

1. **Relevance and Utility**

The extraction of impervious surface area information will be exceedingly useful in urbanization monitoring, population estimation, water quality monitoring, and heat island mitigation analysis. First, building a comprehensive understanding of the density, spatial extent, and patterns of impervious surfaces in Ho Chi Minh City will benefit its urban development and improve its land use accuracy. Son et al. (2012) mapped impervious surface changes with linear mixture model in Ho Chi Minh City between 1990 and 2010 for urban growth analysis. They explored the urban land cover changes between 1990 and 2010 and found that the built-up areas with high albedo expanded from 12.3% in 1990 to 31.1% in 2010. Also, 4.5% of bare soil, 3.5% of vegetation and 2.5% of low albedo classes were all converted to high albedo class between 2002 and 2010 (Son et al).

Second, population growth is usually associated with increasing impervious surface area and decreasing cropland and forested areas. Besides, estimating population based on impervious surface area is reliable and steady because imperviousness analysis will not be influenced by seasonal changes. Lu, Weng, and Li estimated residential population in Marion County, Indiana, by conducting regression analysis model relating impervious surface coverage and population density. They found that this population estimation approach based on impervious surface coverage is better than census analysis with mean and median relative errors of 38% and 23%, respectively (Lu, Weng & Li, 2006).

Third, impervious surface has always been recognized as an important indicator of the health of local water system (Brabec, Schulte & Richards, 2002). Decreasing amounts of forests, wetlands, and cropland resulting from urban expansion directly caused water contamination in local stream and watershed systems from heavy metals and other toxic chemicals carried by a larger quantity of stormwater runoff. Many studies have emphasized a crucial component in quantifying the impacts of impervious surfaces on water bodies: the threshold level of at which degradation in water quality occurs (Arnold & Gibbons, 1996; Schueler, 2000). Based on various threshold levels, Arnold and Gibbons categorized stream health to “protected” (< 10% imperviousness), “impacted” (10%-30% imperviousness) and “degraded” (> 30% imperviousness) (Arnold & Gibbons, 1996).

Lastly, impervious surface area is closely associated to changes in land surface temperature. The rural-to-urban transition during urban expansion has caused both air and surface temperature to rise several degrees. This phenomenon is generally referred as “urban heat island”. Xiao’s research in Beijing, China indicated a clear positive linear relationship between impervious surfaces and land surface temperature (Xiao et al., 2007).

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