LULC Analysis for Sustainable Land Use Planning and Monitoring Using GIS and Remote Sensing

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Abstract

Land use planning in agriculture and environment is highly important to drive sustainable development in the developing countries. The population growth, industrialization and rapid urbanization constantly causing agricultural land use changes, resulting an impact on the ecological balance and food security. Bangladesh is one of the developing countries facing challenges to establish sustainable land use policy for economic development. Land use monitoring are very much lack of and required to practice the legislation from local to regional level while in transition of low lands to urban. A severe decrease of low lands in Dhaka and adjacent sub-districts caused inundation during heavy rain in the pre-monsoon and monsoon seasons. A geospatial decision support considering land use transition, change detection and future projection for Land Use Land Change (LULC) datasets could be an important decision-making process for monitoring land use planning to ensure sustainable agricultural and industrial growths.

The purpose of this research is to develop a spatial decision support system using land suitability analysis to recommend industrial growths policy for protecting agricultural lands and environment. This research also aimed to conduct LULC analysis for sustainable land use planning to monitor the legislation process for protecting agricultural lands and environment.

In this research, satellite remote sensing and GIS based MCA model was developed for land suitability analysis (LSA) to identify the best possible locations of future economic zones in a suburb area of Dhaka city in Bangladesh. AHP-based multi-criteria analysis was used for prioritizing the weights for each of the criteria in LSA. A decision rule and Weighted Linear Combination (WLC) were applied in ArcGIS® to aggregate the criteria weights with the factors and constraints. On the other hand, satellite remote sensing data were used to classify the land use/land cover analysis. Supervised maximum classification technique was applied for the land cover classification and post classification change detection to detect the changes of land covers from 2010 to 2017. In this research, first decreasing of agricultural lands and rapid expansion of industrialization without any assessments of suitability of land uses was reported. Second the study demonstrated GIS, remote sensing and multi-criteria modeling procedures to aggregate expert’s opinions for land use planning for LULC analysis. Third, LSA model was developed to find out the suitable areas for industry expansion. Initially micro level approach was considered with one sub-district, Savar, known for economic zone. Nine criteria: Proximity to major roads, proximity to local roads, distance from rivers, distance from water bodies, distance from settlements, flood flow zones, distance from agricultural lands, slope and elevation were sub-classified into seven constraints and twenty-three factors to perform LSA. AHP-based multi-criteria analysis was applied to incorporate the expert’s opinion for prioritizing the criteria. Weighted overlay was applied in GIS environment to integrate AHP with factors and constraints and classified the research area into four categories: most suitable, moderately suitable, less suitable and not suitable. The land suitability assessment reported only 4% of land was found most suitable for industrial purposes whereas 93% land was not suitable for industrial growths. Furthermore, the most suitable area was further explored to select compact lands to recommend for industrial zones. The analysis found four compact zones having 16.50 ha, 15.17 ha, 10.11 ha and 10.28 ha of lands were suitable for industrial growths in the micro level approach for the sub-district. Fourth, multi-data sources system was incorporated with 1:25000 scale land use maps including Landsat 5 TM and Landsat 8 OLI satellite imageries of 30 m resolution for LULC analysis. The study considered the capital city Dhaka and the surrounding seven sub-districts: Savar, Keranigonj, Narangonj, Bandar, Sonargoan, Rupgonj and Gazipur Sadar. Image preprocessing was conducted for layer stacking, mosaic, sub-setting and image enhancement. The supervised maximum classification was carried out for the land use/land cover classification into seven categories: urban, agricultural high land, agricultural low land, vegetation, natural forest, water-bodies and urban transition. The classified land cover maps showed a radical increase in urban transition of 15.13% in 2017 compare to 2010. In addition, agricultural high and low lands had decreased by 4.67% and 5.23% respectively. Finally, the accuracy level was estimated for the classified maps using user accuracy, producer accuracy, overall accuracy and kappa coefficient from the confusion matrix. The post classification change detection was also applied to understand land cover changes. The accuracy assessments showed that the overall accuracy of the two classified images were 82% and 84% for 2010 and 2017 respectively. The kappa coefficient was 0.8 for both the land cover maps. The change detection showed that approximately 14% land had changed to urban and urban transition from agricultural high land, low land and vegetation.

Present research developed an integrating decision support system using GIS and Satellite Remote-sensing for LULC planning and monitoring for Dhaka and adjacent cities. The land suitability analysis for industrial site selection is a regional demand for developing countries that could be implemented from micro to macro levels. The LULC analysis with the satellite remote sensing has the opportunities to expedite the monitoring system to enhance the legislation and environmental protection of agricultural low lands. Therefore, the developed spatial model using land use maps, satellite data sources could be a guide for policy makers to enforce monitoring system of land use changes for environmental protections and securing agricultural lands for food production.

Keywords: LSA (Land suitability Analysis), GIS (Geographic Information System), MCA (Multi-criteria Analysis), AHP (Analytical Hierarchy Process), Land Use/Land Cover (LULC), Maximum Likelihood (ML), Accuracy Assessment, Change Detection (CD).

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Abbreviations

AHP	Analytic Hierarchy Process
AI	Artificial intelligence
AOI	Area of Interest
BBS	Bangladesh Bureau of Statistics
BGMEA	Bangladesh Garment Manufactures & Exporters Association
BK	Borda-Kendall
BTM	Bangladesh Transverse Mercator System
BUTM	Bangladesh Universal Transverse Mercator
BEZA	Bangladesh Economic Zones Authority
CD	Change Detection
COM	Component Object Model
DEM	Digital Elevation Model
EPZ	Export Processing Zones
ERDAS	Earth Resource Development Assessment System
ES	Expert System
FAO	Food and Agriculture Organization
FIS	Fuzzy Inference Systems
GDP	Gross Domestic Product
HYV	High-Yielding Variety
LGED	Local Government Engineering Department
LSA	Land Suitability Analysis
LULC	Land use and land cover
MCA	Multi-criteria Analysis
MCDA	Multi-criteria Decision Analyzing
MCDM	Multi-criteria Decision Making
ML	Maximum Likelihood

MOLA	Multiple-objective land allocation
NSAPR II	National Strategy for Accelerated Poverty Reduction II
OLI	Operational Land Imager
OWA	Ordered Weighted Averaging
PCC	Post Classification Comparison
RAJUK	Rajdhani Unnayan Kartripakkha
SAW	Simple Additive Weighting
SOB	Survey of Bangladesh
SQL	Structured Query Language
SRTM	Shuttle Radar Topography Mission
SRDI	Bangladesh's Soil Resource Development Institute
SWIR	Short-Wave Infrared Red
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
UN	United Nations
WLC	Weighted Linear Combinations
WGS	World Geodetic System
USGS	The United States Geological Survey

Nomenclature

N1	National Highway
C_{11}	The value of row *i* (the 1st row) and column *j* (the 1st column) in the pairwise comparison matrix
X_{ij}	The normalization matrix of pairwise comparison matrix of AHP
W_{ij}	The weight matrix of AHP
λ_{max}	Principal eigenvector
CI	Consistency Index
RI	Random inconsistency index
n	Number of criteria
S_i	Suitability Index
X_i	The score of each factor and constraint
U	Urban
Agri HL	Agricultural High Land
Agri LL	Agricultural Low Land
V	Vegetation
FS	Forest Sal
WB	Water-bodies
UT	Urban Transition
R	Red
G	Green
B	Blue
$P(i\|\omega)$	Posteriori distribution
$P(\omega\|i)$	Likelihood function
$P(i)$	Priori Information
$P(\omega)$	The probability that ω is observed

M	Number of classes
N	Number of sample size
p	The expected percent accuracy
q	100-p
E	Allowable error
K	Kappa Coefficient
x_{ii}	The number of observations in row i, column i
x_{i+}	The total number of observations in row i
x_{+i}	The total number of observations in column i,
N	The total number of observations in matrix

CHAPTER 1
Introduction

1.1 Land Use Planning

Land use planning is an indispensable domain of sustainable development. Food security, environmental protections, global climate change, growing population are the main driving forces to achieve a sustainable land use planning. Regional to global level human activities has increased on the earth surface to sustain and to improve the quality of life. Hence, the challenges to secure land resources have increased more compare to opportunities and scopes for balancing the ecosystem and human needs. Therefore, land use planning has significant importance in the current era and for future generations. Considering the tremendous pressure and diverse phenomenon in terms of challenges, scopes and requirements for land use, FAO had defined the land use planning. It states, “Land use planning is a systematic and iterative procedure carried out in order to create an environment for sustainable development of land resources. Land use changes assesses the physical, socio-economic, institutional and legal potentials and constraints with respect to an optimal and sustainable use of land resources and empowers people to make decisions about how to allocate those resources (FAO/UNEP 1999: 14)”. The statement had achieved global recognition from government to institutional organizations and practitioners of land use planning as a response to current obstacles and challenges for development.

In response to the global concern for land use planning, regional activities should be aligned to obtain the sustainable land use planning. It is evident that the core elements of the land use planning are, to balance the land resources, fulfil people’s demand, legislation system and enable the people to make feasible decisions. The regional stakeholders should follow the norms and general requirements to design a comprehensive land use planning and to implement the legislation. However, it is challenging to overcome the barriers and to execute the requirements of the land use planning. Different regions have their own limitations specially for the developing countries where resources are limited compare to the adverse scenarios against land use management. As a result, the regional land use planning fails to fulfil the local public demands and cannot contribute for the international development goals.

Bangladesh, well known as an agrarian country, one of major rice production hub of the world and also densely populated country is now facing challenges for securing a sustainable land use planning. There is constant pressure on the land resources to increase the food production and also for the economic developments. Due to the lack of policy planning and legislation systems there is land conflicts resulting land use changes in inappropriate manner. The continuous land use changes had affected the local food production and creating an adverse environment for the inhabitants.

1.2 Land Use Changes in Bangladesh

Bangladesh has very productive land and the weather is suitable for agriculture. Approximately 60% of the land is used for cultivation (Rai *et. al*., 2017). However, the agricultural land had declined, and non-agricultural activities had increased over the past few decades (**Figure 1.1**). Studies showed that at the national level Bangladesh had 67.38% of agricultural land in 1976 which had gone through land transformation of approximately 0.13–1% per year (Hasan *et. al.*, 2013). World Bank reported that Bangladesh had lost agricultural land and the trend was downward (**Figure 1.2**). On the other hand, the urban and industrial areas were occupied 26,799 ha in 1976 which increased to 1,644,300 ha in 2014 (Reddy *et. al.*, 2016). The highest growth of urban areas was found in the center of Bangladesh, Dhaka. The capital city had experienced a significant hike in urban growth from 11 to 344% between 1960 to 2005 (Dewan and Yamaguchi, 2009). In addition, Dhaka division had last 1.45% of agricultural lands annually which was higher than the rest of the country (Quasem, 2011).

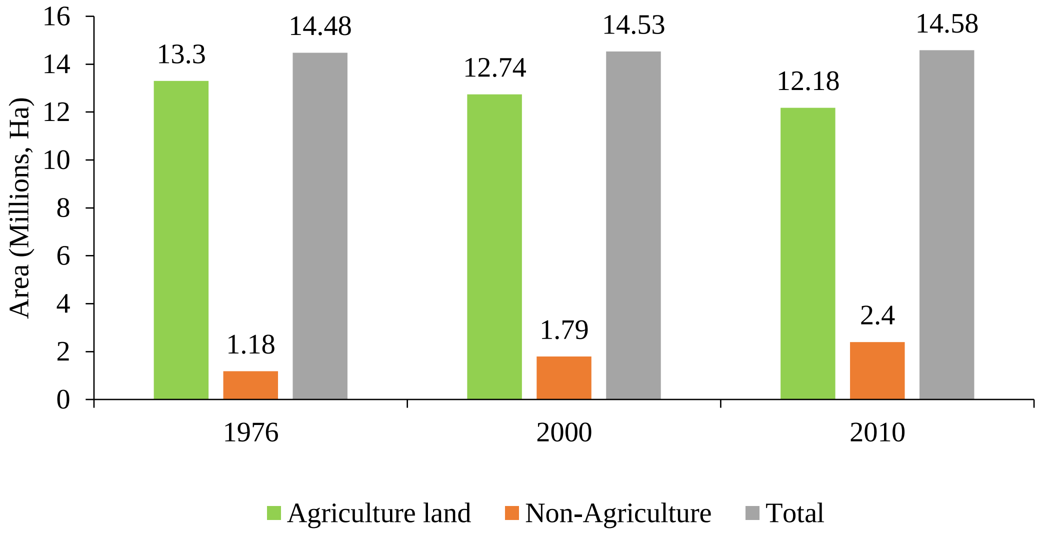


Figure 1.1 Agricultural land and non-agricultural land use status between 1976 to 2010 (Source Hasan *et. al*., 2013)

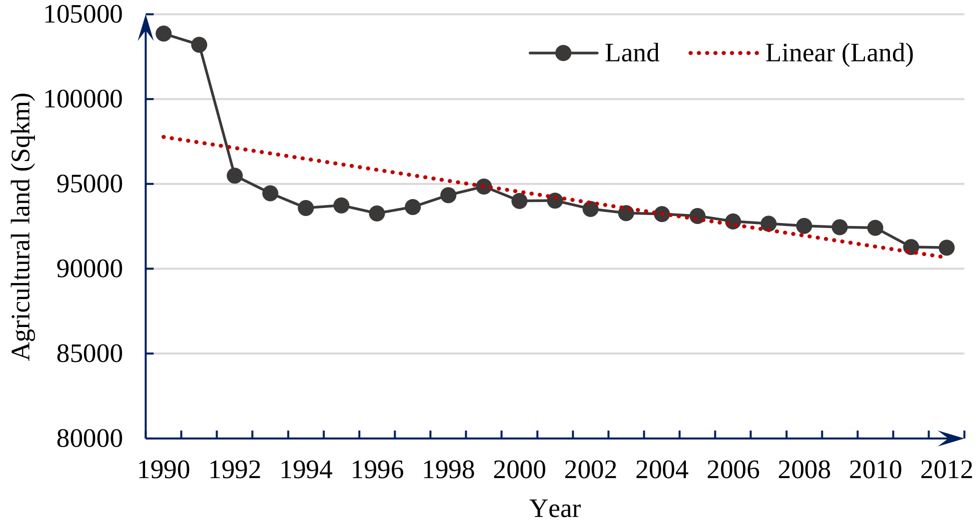


Figure 1.2 Agricultural land use from 1990 to 2012 (World Bank).

1.3 Driving Forces for Land Use Changes

The major reasons for agricultural land decline are transformation of agricultural lands to industrialization and urbanization. The economy of Bangladesh has groomed over the last few decades. In the global market, Bangladesh has recognized as second largest exporter of ready-made garments. International brands such as UniQLO, GAPS, Walt-mart, Targets, H&M, Primare are the major buyers of readymade cloths. Industry contributes potential service for economic development, which covers approximately 30% of the national GDP of Bangladesh. According to Bangladesh export items of FY 2012-13, 80% of the foreign earnings came from the cloth industry whereas agricultural products contributed only 2% **(Figure 1.3).** It is evident that that main purpose of the food production is to fulfill the local demand. Considering the economic benefits, the local and foreign investors are more likely to invest in the ready-made garments business. To increase the GDP growth rate government encouraging to build up industrial zones in every possible locations. Therefore, the average cloth export growth rate was more than 17% over the last two decades. As a result, the number of factories had increased significantly, approximately average 4% every year **(Figure 1.4).** Among the existing industries, more than half of the industries is located in Dhaka and adjacent sub-districts and had built up in last couple of decades. Thus, the growth of the industries and the declination of the agricultural lands within Dhaka and its peri-urban areas is the evident that the growth of industry is one of the driving forces for the agricultural land transformation.

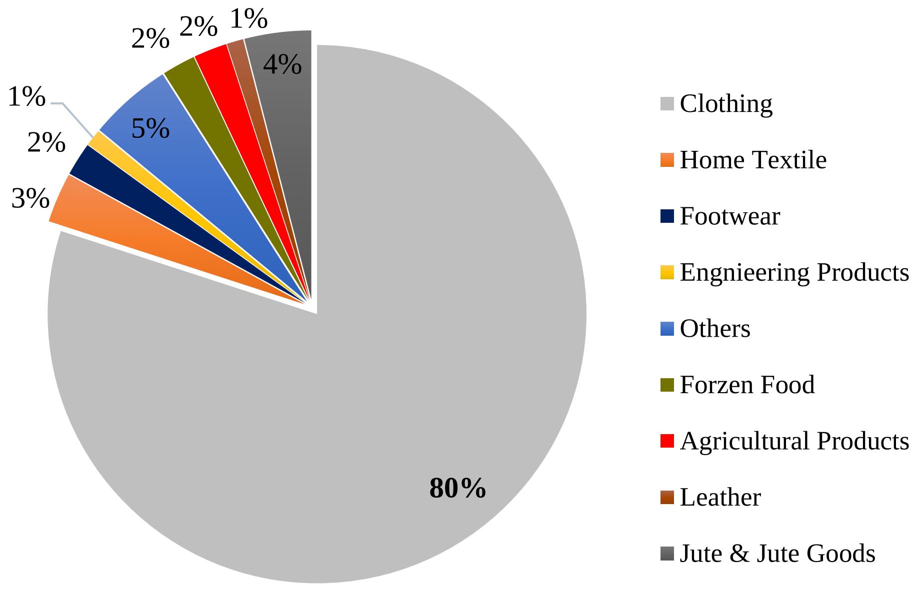


Figure 1.3 Bangladesh export items FY2012-13 (Source: BGMEA, 2014).

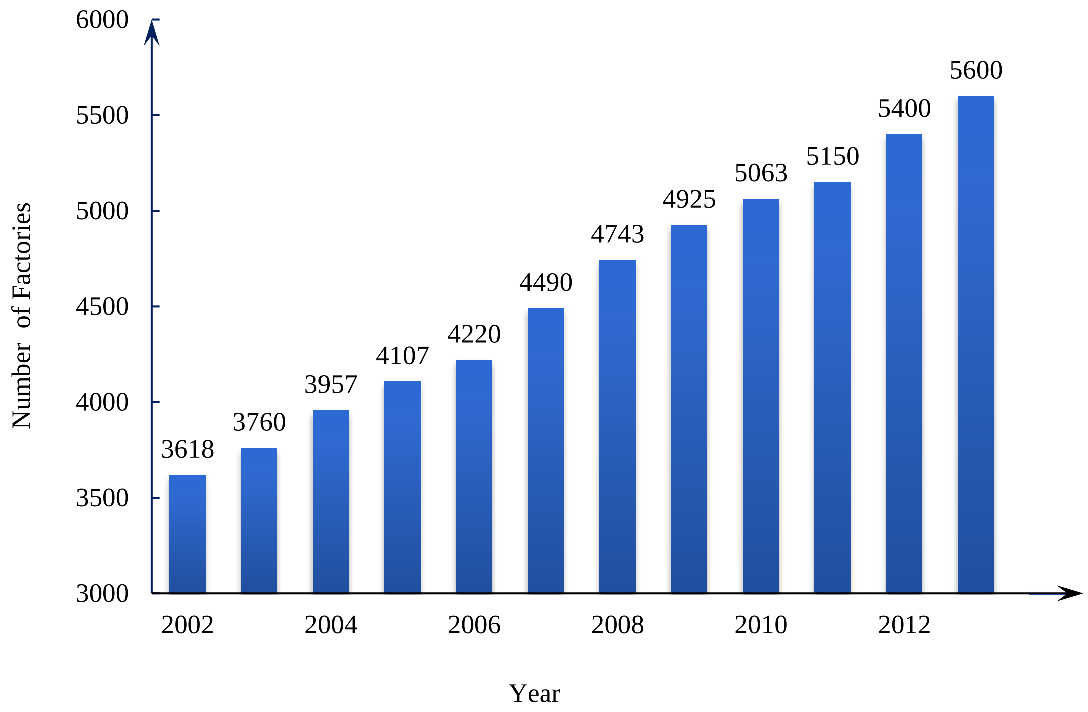


Figure 1.4 The growth of the cloth factories in Bangladesh (Source: BGMEA, 2014).

In addition, the recent years had observed massive urban developments in Dhaka and its fringes. The city was the second densely populated city in the world in 2016 **(Table 1.1).** The city had occupied with urban settlements and rarely could found any open space for further urban development. However, the population migration is in a rapid pace in Dhaka from districts level to country side area mainly for livelihood and education. Thus, the GDP growth has increased in Dhaka and centralized the economy. Due to the excessive population pressure, Dhaka has expanded in all directions, occupying the adjacent sub-districts land resources. The urban transition had grown on mainly by self-ownerships, privately owned companies and different organizations of Bangladesh government. The residential area dominates the most comparing with commercial areas and service sectors. Government also building residential areas as small town in the fringes areas of Dhaka. Purbachal, Uttara 3rd phase, Jhilmil projects were taken by the government to accommodate the people.

Table 1.1 The world megacities in 2016 (UN, 2016).

Rank	City, Country	Population in 2016 (thousands)	Population Density Rank	City, Country	Population in 2030 (thousands)	Population Density Rank
1	Tokyo, Japan	38140	6	Tokyo, Japan	37190	6
2	Delhi, India	26454	5	Delhi, India	36060	4
3	Shanghai, China	24484	10	Shanghai, China	30751	10
4	Mumbai (Bombay), India	21357	4	Mumbai (Bombay), India	27797	3
5	São Paulo, Brazil	21297	9	Beijing, China	27706	11
6	Beijing, China	21240	11	**Dhaka, Bangladesh**	**27374**	**1**
7	Mexico City, Mexico	21157	8	Karachi, Pakistan	24838	9
8	Osaka, Japan	20337	1	Al-Qahirah (Cairo), Egypt	24502	2
9	Al-Qahirah (Cairo), Egypt	19128	3	Lagos Nigeria	24239	5
10	New York, USA	18604	7	Mexico City, Mexico	23865	7
11	**Dhaka, Bangladesh**	**18237**	**2**	São Paulo, Brazil	23444	8

1.4 Consequences of Land Use Changes

Agricultural land use change for non-agricultural use directly affect the food production and could be a threat for food security. A study was conducted in the six divisions of Bangladesh to assess the farmland conversion status from 2001 to 2008 by collecting 100 samples farmlands from each division (Quasem, 2011). This study reported that 90% of the agricultural lands that transformed to non-agricultural purposes, were crop lands. In addition, study also found among the six divisions, Dhaka had lost 95% of the crop lands considering the sample farmlands in the study area. The farmlands were mostly paddy fields and in total the production loss per annum was 273 USD per acre. This was a concerning issues for the land use policy makers and observed a legislation deficiency at the local level.

Further, the change of the agricultural lands to non-agricultural purposes due to industrialization and urbanization has triggered the environmental risk. The urban areas are expanding in Dhaka cities and its outskirts more than any other cities of Bangladesh. Providing accommodation of the growing populations of this city became one of reason of urban land transformation. Government and realtors are running different projects for developing residential areas. Since Dhaka is surrounded by the major rivers, the outskirts areas of Dhaka are low lands. In addition, these areas are flood plain areas which during the monsoon inundated with water. In addition, Dhaka is in the downstream area for the larger rivers coming from the Himalaya. Thus, during the monsoon the water flow rate is high. In dry season these flood plains were used for agricultural purposes. Due to land conflicts these lands were transformed into urban residential areas. Researches and reports from different organizations had reported that Dhaka had lost low lands. As a consequence of the low land transformation, water cannot flow in its natural way and causes flood and inundation during heavy rainfall (Figure 1.5).

On the other hand, the industries are mostly privately financed and scattered from the city to sub-urban areas. There are few economic zones which are separated from the other urban areas. The rapid expansion of the industries providing the opportunities of employment but degrading the agricultural lands of the suburban areas. The industrial growths on agricultural lands in the suburb areas are being increased without any suitability assessments. As a result, the industries are one of reason for environmental hazards.

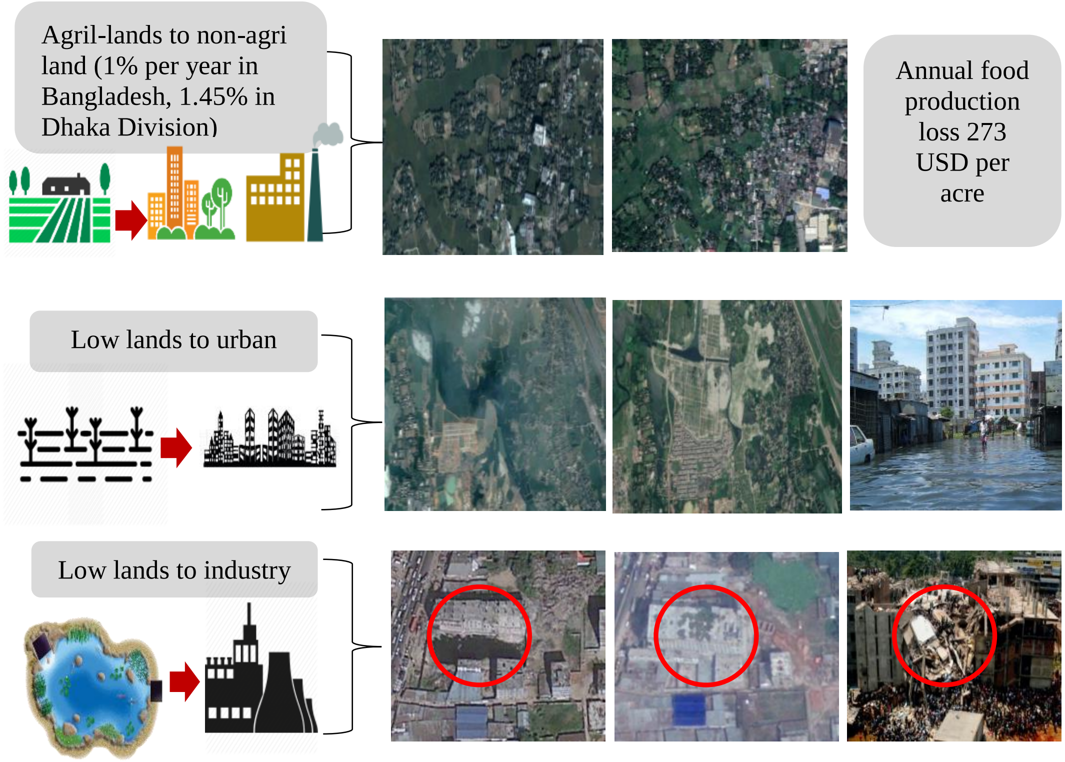


Figure 1.5 Land use transformation causes food production loss, inundation and fatal accidents.

1.5 Problem Statement

Agricultural land use changes and transition of land use to industrial transformation in the suburban areas of Dhaka City becomes a concern for environmental protection in Bangladesh. Rapid changes of low agricultural lands to the urban transition in Dhaka and adjacent areas reduced the retention areas and creates inundation during heavy rainfall in the monsoon period. The lack of policy and absence of geo-reference-based management have been identified one of the major problems of land use planning. Industrial growth in the sub-urban areas expands without any environmental regulations. Therefore, the land use changes require geo-referenced site selection system for industrial growth which can secure agricultural land in the suburban areas. Furthermore, a legislation system is also required to monitor land use change dynamics for preventing inundations during heavy rainfall in Dhaka City.

1.6 Research Question

- What would be the spatial solution in land use planning for industrial expansion in suburban areas of Dhaka City driving the factors of environmental regulations, securing agricultural lands, prioritizing expert's opinion and optimizing the efficiency of land use?
- How to ensure spatial monitoring system in suburban areas of Dhaka City to empower the legislation process, protecting land transformation and to prevent inundation?
- What is the spatial pattern of land use change dynamics and how the spatial pattern of land use could serve for environmental conservation?

1.7 Research Objectives

Therefore, the land use planning is one of the core domains of regulatory and policy planning for sustainable development of a society. The vision of the land use planning is to allocate the available land resources to make the best output from that land consistent with the environmental protections and food security. Furthermore, land use planning could propose the future growth of industries considering legislation and safety and economic benefit. Remote sensing and GIS is best spatial analysis tool to incorporate in the land use planning. In Bangladesh, very few studies were done on the urban expansion monitoring. In addition, there were not many researchers done on the mixed land-use area to evaluate the capabilities of the medium resolution optical images like Landsat. Considering land use policy and industrial growth, urban expansion and enforced the land use change protection, the following objectives considered in this research:

- To develop a suitable site selection system for industrial growth and analyze agricultural land use changes in a micro level focusing a sub-district in the suburban areas adjacent to Dhaka City.
- To perform a LULC analysis system using time series remote sensing satellite images in macro scale covering all sub-districts of suburban areas including Dhaka City.
- To perform a LULC change detection in macro scale for all sub-districts of suburban areas including Dhaka City.

1.8 Outline of the Thesis

Chapter 1 attempted to state the current problems related to land use of Bangladesh. Based on the statistical data, it is evident that Bangladesh is losing agricultural lands whereas there is a significant increase in urbanizations and industrialization in the recent decades. The land use transformation affecting the agricultural lands which is a challenging issue for sustainable development of land use. A possible approach for developing the land use process is to applying suitability analysis for specific land use type according to the attributes of land and integrating the stakeholders concern.

Chapter 2 illustrates the basic concepts of different spatial modelling for land suitability analysis. The broad discussion of the advantages and disadvantages of the spatial modelling assisted to choose the best approach for multi-criteria modelling for the land suitability analysis. In addition, the chapter also describes the application of GIS in spatial modelling. GIS is an indispensable part for any spatial modelling which help the decision makers to implement the scientific knowledge in conjunction with the real-world scenario.

Chapter 3 successfully applied the land suitability analysis to find out the suitable areas for industry expansion. The research was conducted in micro level, considering one sub-districts which is known for economic zones for industries. Criteria and factors and constraints were selected for the land suitability analysis. AHP as a multi-criteria analysis were applied to incorporate the expert’s opinion to prioritizing the criteria. Weighted overlay in GIS environment was applied to integrate the AHP for factors and constraints. The study found that maintaining the environmental regulations, restrictions and protecting the existing agricultural lands, the study area does not carry enough lands for industrial expansions. In fact, the study area already experienced an urban transformation from agricultural lands. Thus, further study is required to understand the land use pattern of the study area.

Chapter 4 applied satellite remote sensing application for LULC analysis. The study considered the capital city Dhaka and the surrounding seven sub-districts including the Savar area. The supervised maximum classification approach had applied for the land use/land cover classification. The recent decade had considered to map the land covers using the Landsat TM and Landsat OIL sensor data for 2010 and 2017 respectively. The land covers of 2010 and 2017 showed that an urbanization had took place during the study period at a rapid pace and there were a declined in agricultural lands. However, the accuracy assessment was required for the classified maps for further analysis.

Chapter 5 attempted to assess the accuracy level of the classified maps. The accuracy was found deemed acceptable for both the LULC maps. Thus, post classification change detection was done for the classified images to find out the spatial pattern and thematic changes of the individual land classes. The change detection also found that the urbanization had took place mainly by transforming the agricultural lands and vegetation.

Chapter 6 illustrated the overall conclusion of the research. The research demonstrates a spatial solution for the land use planning which suggest implementing GIS and remote sensing applications for find out best possible land resources for any urban development, incorporating the environmental ethics and regulations.

CHAPTER 2

Review of Literatures

2.1 GIS-based land suitability analysis methods

GIS based land suitability analysis is a widely used approach now a day. In the late nineteenth and early twentieth century, American landscape architects used to do hand-drawn overlay techniques which is the base of today's modern approach to use GIS in land-use suitability analysis (Malczewski, 2004). Basically, there are three groups of approaches to GIS-based land use suitability analysis (1) computer-assisted overlay mapping, (2) multi-criteria evaluation methods and (3) AI (soft computing or geo-computation) methods.

2.1.1 Computer-assisted overlay mapping

The computer-assisted overlay mapping techniques enable to keep the models in numerical form as matrices in the computer instead of mapping the values manually in a series of suitability factors in gray or any colour scales. Once the maps are formed then individual maps can be analyzed and accumulate to get the overall suitability map. Many researchers have used and developed this method integrating many techniques to fulfill their objectives in land use problems. Among these maps overlay approaches, the Boolean operations and weighed linear combination (WLC) application became very popular due to its simple appliance in GIS environment using map algebra operations. However, it is observed that while dealing with a number of facts of land use planning, this approach fails to focus on the correct combination of facts and to employ value judgments for the facts. The presentation of such complex phenomenon in computer environment and in GIS are difficult. This drawback can be overcome by using GIS and multi-critria decision making/Analysis (MCDM/MCDA) methods.

2.1.2 Multi-criteria evaluation methods

Multi-criteria decision-making methods is a branch of a general class of operations research models. These methods are suitable for addressing complex problems featuring high uncertainty (Mateo, 2012). GIS-based MCDA method is described as a procedure that accumulate and transforms spatial and a spatial data (input) into a resultant decision (output) (Malczewski, 2004). The MCDA method built a connection between input map and output map by utilizing the geographical data, judgement values of decision makers upon the facts and correlate with the specified decision rules. Multi-Criteria Decision Analysis (MCDA) is a general term for systematic and transparent approaches to analyze complex problems involving multiple criteria (Mustajoki and Marttunen, 2013).

The multi-criteria decision analysis has been used by different stakeholders in different scenarios to simplify a complex analysis and to derive a solution. Thus, the usage of this method enables a variety of other methodologies to incorporate and solve problems of different circumstances. Malczewski (1999) in his book, illustrate three opposite characteristics methods under the umbrella of MCDA. They are - (i) multi-objective (MODM) versus multi-attribute decision making (MADM), (ii) individual versus group decision-maker problems and (iii) decisions under certainty versus decisions under uncertainty. Another important one is multi-attribute utility theory (MAUT). Multi-attribute utility theory is an extension of utility theory developed to help decision-makers assign utility values, taking into consideration the decision-maker's preferences, to outcomes by evaluating these in terms of multiple attributes and combining these individual assignments to obtain overall utility measures. Utility theory has generally been used to develop a relationship between utility and costs incurred as a consequence of a particular decision (Mateo, 2012). These wide and rich varieties of techniques and procedures enable decision makers to express their preferences and combine them with GIS- based decision making.

2.1.3 Artificial intelligence (AI) methods

The developments in spatial analysis has brought a new prospect in the land-use suitability analysis and planning by using AI (computational intelligence). It can be defined as, AI includes the modern computational techniques that can help in modeling and describing complex systems for inference and decision making Malczewski (1999). Soft computing is the major area of AI which can enable AI to develop systems which could mimic human intelligence. And for this, AI do not need to understand the inherent decision rules. Thus, it is flexible to tolerant uncertainty, fuzziness, and partial truth which is not feasible in conventional approaches.

2.2 Overview on Multi-objective and Multi-attribute Analysis

An **objective** is a statement about the desired state of the system under consideration. Basically, it is associated with the attributes which need to improve to fulfill the objective. On other hands, an objective is a more abstract variable with a specification of a relative desirability of the levels of that variable (Drobne and Lisec, 2009).

On the other hand, an **attribute** are the properties of elements of a real world geographical system. In other words, an attribute is a measurable quantity or quality of a geographical entity (Malczewski, 1999). In the multi-criteria methods it is assumed that the number of alternatives is explicit. In this type of problems, the choices are made among the alternatives described by their attributes. These reflect that the relationships among attribute-objective are stated in a way that the attributes are considered both objectives and decision criteria. (Malczewski, 1999; Drobne and Lisec, 2009). Thus, these two discrete approaches are used in different cases. If the problem is to asses a finite number of possible set of alternatives and to select the best one based on the scores of a set of attributes, it is MADM (Phua and Minowa, 2005). On the contrary, MODM is used to select the best alternatives based on a series of conflicting objectives (Massam, 1988; Phua and Minowa, 2005). The model for this procedure is based on mathematical programming and here the alternatives are identified by solving a multi-objective mathematical programming problem.

Normally, MADM approached are searched-based approaches and use raster-based data structure while using in GIS. On contrary, MODM are choice-based approaches which is used in vector-based data structure. While processing a model if there is any direct correspondence between attributes and objectives then the multi-objective problem becomes a multi-attribute problem. In addition, the attributes are used both as decision variables and decision criteria in multi-attribute decision analysis (Drobne and Lisec, 2009).

In addition, the subdivision of the multi-criteria decision problems, individual and group decision can also apply to both MADM and MODM. The drawback of MODM is described as, in practice, it is often deal by converting the MODM model to single objective problem and then the problem is solved by standard linear/ integer programing methods. In context, the MADM approaches are considered as much easier to apply in GIS especially for raster data model (Malczewski, 2004).

MADM method has been incorporating with a number of techniques over the last three decades. The most used and popular methods are-

2.2.1 Boolean overlay

It is an intersection of binary coded layer which is derived by the application of Boolean operations like AND, OR, XOR and NOT. The resultant data layer in this process shows areas that are 'true' which fulfill the decision rule and rest as 'false'. This method is typically used in vector data layers (Eastman, 1999).

2.2.2 Weighted Linear Combination (WLC)

The process is also called simple additive weighting which is based on weighted average concept. Here the decision maker assigns the weights of 'relative importance' to each attribute map layer directly. The total score is obtained for each alternative by multiplying the importance weight assigned for each attribute by the scaled value given to the alternative on that attribute and summing the products over all attributed. After obtaining the overall score for all alternatives, the highest overall score is selected. This method can be conducted in GIS environment by the application of overlay operation. This operation is capable to combine all the criteria maps, treated as input layers, under evaluation to derive the composite map or suitability layer as output. After that it may be then masked by one or Boolean constraints to derive a qualitative criterion and therefore the final layer is produced. The advantage of this method is that it is applicable in both vector and raster data.

2.2.3 Ordered Weighted Averaging (OWA)

To eliminate the limitations with Boolean overlay and WLC, Jiang and Eastman in 1996 have introduced an extension of Yager's (1988) Ordered Weighted Average to GIS for Multi-Criteria Evaluation. The process has two set of weights, one is criterion importance weights and other is order weights. To specify the relative importance based on the decision-maker's preference, an important weight is assigned to a given criterion (attribute) for all the locations in the study area. On the other hand, the order weights are related to the criterion values on a location-by-location (object-by-object) basis. The order weights are related to a location's attribute values in descending order where the process does not consider the attribute value's source. The order weights are the core of the OWA combination procedures. These are related to the degree of ORness, which reflect the degree to which an OWA operator is similar to the logical connective OR in terms of its combination behavior. The parameter is also related to a trade-off measure which indicate the degree of compensation between criteria. The parameters associated with the OWA operations serves as a mechanism for guiding the GIS-based land-use suitability analysis (Malczewski, 2004).

2.2.4 Analytical Hierarchy Process (AHP)

The Analytical Hierarchy process which is introduced by Saaty in 1980, is now a very powerful method along with the GIS.This method can be used in two different process according to the individual case. First, the method can be used to derive the weights related with the suitability (attribute) map layers. After that, the weights can be combined with the attribute map layers by the same way as to linear additive combination methods. This approach is of particular importance for the problems involving large number of alternatives represented by means of the raster data model, when it is impossible to perform a pairwise comparison of the alternatives (Eastman *et al*., 1993). Second, the AHP principle can be used to aggregate the priority for all level of the hierarchy structure including the level representing alternatives. In this case, a relatively small number of alternatives can be evaluated (Banai, 1993; Jankowski and Richard, 1994). Jankowski (1995) stated that the AHP is more suitable to implement in vector-based GIS. The important aspect of AHP is, it can be used as consensus building tool in the cases of group decision making or committee (Saaty, 1980).

AHP is a technique in MCDA analysis which offer a scope to involve expert opinions, group discussions and individual judgments to evaluate the criteria and their relative preferences. AHP is now recognized as a powerful decision support tool which is able to solve complex decision problems. AHP has the capability to analysis a problem in a systemic way and evaluate the problem comprehensively. The main hierarchy structure of AHP consists with a goal, criteria and alternatives **(Figure 2.1).**

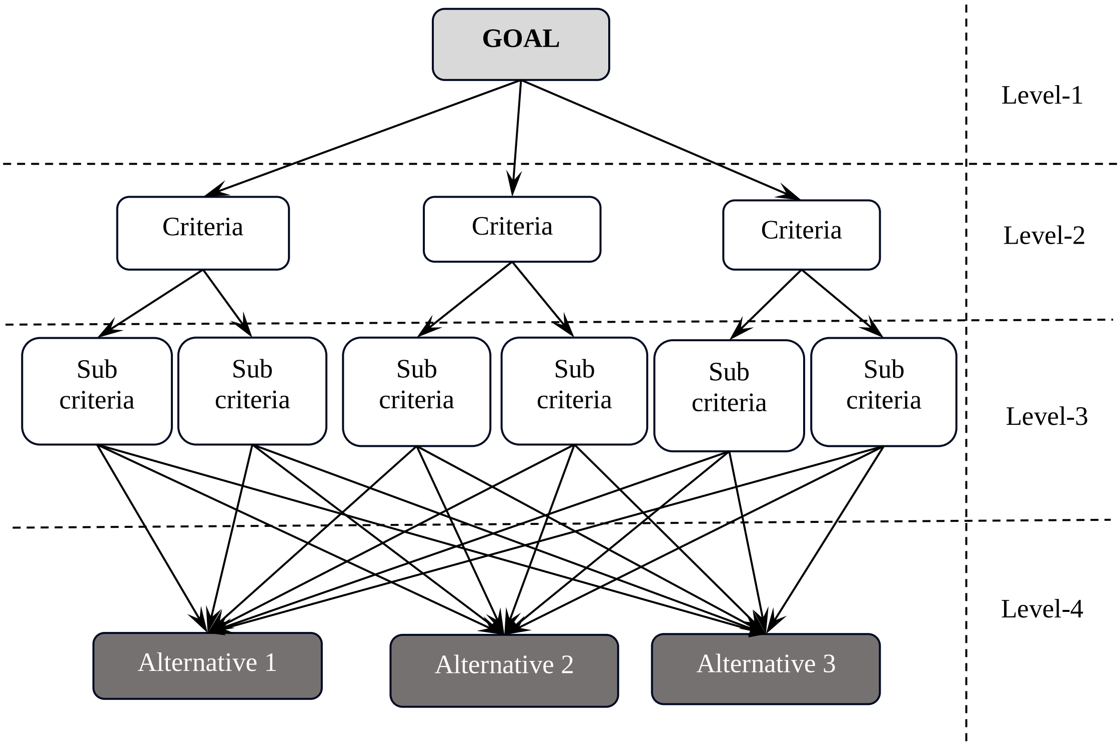


Figure 2.1 Multi-level hierarchy structure of AHP.

2.3 Multi-Criteria Evaluation/ MADA

Multi-Criteria Evaluation also called as multi-attribute evaluation or Multi-Attribute Decision Analysis (MADA).

Step 1: Define the problem/ set goal and objectives

The starting point of any decision-making problem is to clearly state the problem or to set a goal. It could be a set of goals depending on the interest of stakeholders or individual interest. The goal and objectives highly depended on the understanding of the problem by the actors. In management, there is a **S.M.A.R.T**. way described by Doran (1981) to set any goals and objectives.

S- Specific- target a specific area for improvement.

M- Measurable- quantify or at least suggest an indicator of progress.

A-Assignable- specify who will do it.

R- Realistic- state what results can realistically be achieved, given available.

T- Time –related- specify when the results can be achieved.

In the multi-criteria decision analysis, the elaboration of S.M.A.R.T. could help to set the goals and objectives in individual content.

Step 2: Selection of criteria (factors and constraints)

The criteria have to select in a way which can measure the performance relative to the objectives. That's why it is very important to perform the first step of the multi-criteria analysis. Then it would be easier to select the criteria which can relate the goal and objectives precisely and in a comprehensive manner. A comprehensive understanding on the meaning and explanation of such important element of a process should be kept in mind while performing any MCDA.

Criteria: A criterion is some basis for a decision that can be measured and evaluated. It is the evidence upon which an individual can be assigned to a decision set (Beinat, 1998). Criteria can be of two kinds: Factors and constraints and these can relate to attributes of the individual or to an entire decision set. For **example**: in a general land suitability case, the most common criteria are- slope, elevation, land use etc.

Factors: A factor is a criterion that enhances or detracts from the suitability alternative for the activity under consideration (Beinat, 1998). Thus, factors are always measured on a continuous scale. **Example**, if the goal is set to find a land for establishing a restaurant, then it would be very important to find the land near to a densely populated area. So, the number of people near the land is very important for such case. The probability of the business profit would increase with the number of people living around the area.

Constraints: A constraint serves to limit the alternatives under consideration (Beinat, 1998). For **example**, to find a suitable waste disposals area, there should not be any settlement within 100 kilometers of the area. Another good **example** would be excluding any area for any development for the conservation of forest and wildlife. Most of the cases, the limitation of such restriction set out by the local government or it could be a reasonable assessment on the environment perspective of the local area. Most of the time, constraints are stated in a Boolean (logical) map where the areas are eliminated from consideration by coding with a 0 and rest which are needed for consideration are coded with a 1. Constraints could also be stated in a way that the decision set must process it to fulfill the goal. Example can be expressed as, among the suitable areas for establishing a University, an authority need not less than 1000 hectares of land. The main purpose of the constraints is to exclude the options under consideration.

Step 3: Determine weights of each criteria

In this step all the criteria (factors and constraints) need to assign weights. There is a number of methods to conduct this stage such as Analytical Hierarchy Process (AHP), Weighted Linear Combination (WLC), The Ordered Weighted Average (OWA). Depending on the individual scenario and defined goal, combination of such techniques can also have applied to compare the whole process. The weight of each criteria reflects the relative importance of each criteria under consideration in the multi-criteria decision making. It is very important to select the appropriate method in order to rank the alternatives. The data and the degree of uncertainty are key factors for the decision-maker when selecting among several multi-criteria methods (Dodgson *et. al*., 2009). At the end of this process a decision matrix could be created to express the MCDA problem. This is the central element of MCDA (Malczewski, 1999).

$$\text{Criteria} \quad C_{1,} C_2, \dots\dots.., C_n$$

$$\text{Weights} \quad W_{1,} W_2, \dots\dots, W_n$$

$$\text{Alternatives}$$

$$\begin{bmatrix} A_1 \\ \vdots \\ A_m \end{bmatrix} \quad \begin{bmatrix} x_{11} & x_{12} \cdots & x_{1n} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} \cdots & x_{mn} \end{bmatrix}$$

Where x_{ij} is the evaluation given to alternative i^{th} with respect to criterion j^{th}, w_j is the weight of criteria j, n is the number of criteria and m is the number of alternatives (Dodgson *et. al*., 2009).

Step 4: Define a decision rule to combine the criteria

In this step, all the criteria are combined by giving them a score. For this, a decision rule is set for the process.

Decision rule: A procedure by which criteria are combined to arrive at a particular evaluation, and by which evaluation are compared and acted upon, is known as a decision rule (Beinat, 1998). Decision rule could be simple to apply only on one criterion for example in the land use suitability analysis the decision rule might be stated as only plane land in the land use thematic map among other land types as agriculture, forest, hilly area would be suitable for any development. However, in MCDA it would be a complex rule to combine all the criteria into a single composite index by multiple procedures.

Step 5: Verify the result

The last but not the least, step is to verify the result. Ground truth verification by means of conducting a field survey on the resultant area. Here, samples can be selected if the result showed a number of suitable places. Another process can be run as a means of sensitivity analysis. Here the whole process run again by manipulating the criteria or on the weights of the factors to see whether the result is reasonable. The basic steps of a multi-criteria analysis are given in **Figure 2.2**.

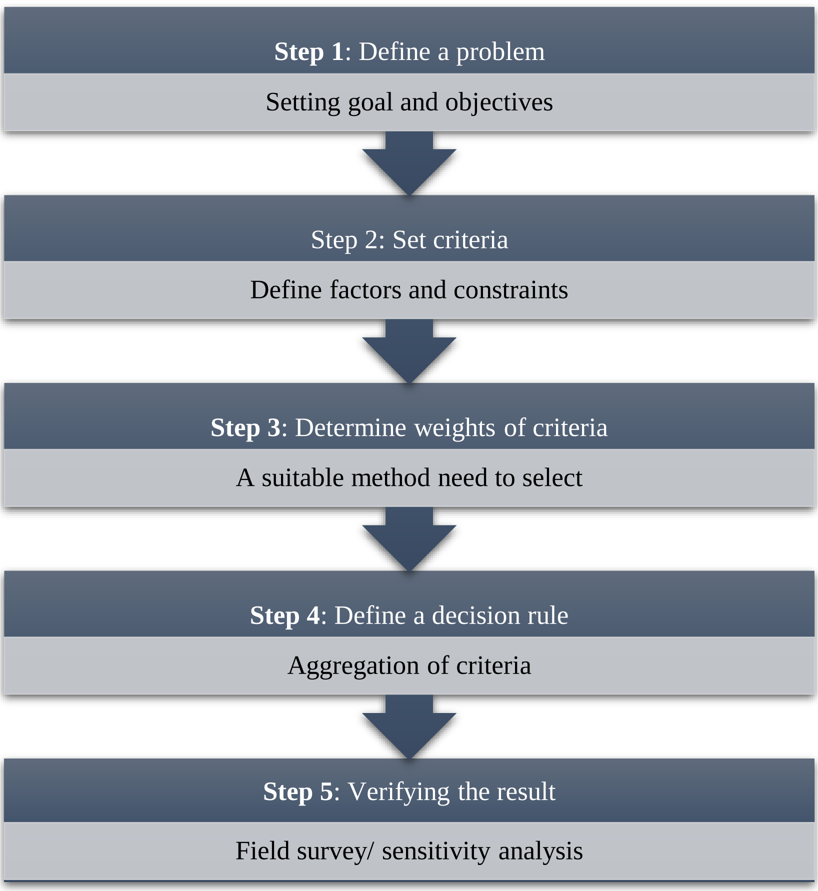


Figure 2.2 Basic steps of Multi-criteria decision analysis.

Chapter 3

Suitability Mapping for Industrial Growth in sub-district of Suburban Areas (Micro-Scale)

3.1 Background

Land use changes significantly affect the sustainability of food security, ecological balance and environmental protection in developing countries. To compensate for land losses and the degradation of the best lands, the usage of fertilizer has increased to improve crop production and the yield per hectare, which is deteriorating energy efficiency (Tong, 2003). Bangladesh is the 10^{th} most densely populated country in the world with 1237 people per sq. km of land area (World Bank, 2015), faces similar challenges from limited arable land resources. Thus, agricultural land use has become an important domain for sustainable development to feed an increasing population. However, studies have noted that the agricultural lands of Bangladesh have decreased over time. Aerial photographs and Landsat imageries were analyzed by Bangladesh's Soil Resource Development Institute (SRDI) to determine this land transformation. Approximately 0.13% of agricultural land was transformed to non-agricultural land per year from 1963 to 1983 (Rahman and Hasan, 2003). The Rio + 20: National Report on Sustainable Development also mentioned that Bangladesh has lost 1% of its agricultural land every year to non-agricultural purposes (Bangladesh Ministry of Environment and Forests, 2012). In addition, one study that utilized satellite images and GIS stated that Bangladesh had lost 23,391 ha of agricultural land per year from 1976 to 2000. This annual loss increased drastically to 33,140 ha during the period of 2000-2010, resulting in a total of 8% of agricultural land losses from 1976 to 2010 (Hasan *et. al*., 2013). On the contrary, this study also indicated that the total urban and industrial area had increased from 26,799 ha to 87,616 ha from 1976 to 2010.

The loss of agricultural land and increasing land area for urbanization and industrialization are causing unsustainable land use practices. These industries have expanded from city areas to suburban areas and occupied agricultural lands, creating a major challenge for food production in the long run. Because of the lack of availability of land, NSAPR II (National Strategy for Accelerated Poverty Reduction II) emphasized developing efficient land markets and modern economic zones to improve land use management and to achieve environmentally and socially compliant industrialization (Planning Commission, 2009). Furthermore, referring to the Bangladesh Economic Zones Act (No. 42 2010), Bangladesh Economic Zones Authority (BEZA) aims to establish economic zones in all potential areas of Bangladesh including backward and underdevelopment regions. In addition, according to this act, the government could notify the official gazette, to select any specific land area and could declare it as an economic zone. Since the economy is in the growing stage, there is a high possibility of land encroachment across the country to establish industrial and manufacturing sectors. However, priority should be given to protect existing agricultural lands and environmental issues while identifying any suitable land sites. In this regard, land suitability analysis (LSA) could be the most appropriate approach to evaluate and fulfill the required criteria for these facilities. Therefore, the hypothesis of this empirical research is that the suitable site location of the industry for economic growth could reduce the pressure of transformation of agricultural lands to scatted expansion of industries throughout the suburb areas.

LSA is a tool that is used to identify the most suitable places for locating future land uses (Collins *et. al.,* 2001). Land-use suitability analysis identifies the most appropriate spatial patterns for future land uses according to specific requirements, preferences, or predictors of some activity (Malczewski, 2004). In other words, LSA is a spatial decision-making process where a number of elements are evaluated to conform to the requirements of stakeholders and environmental issues.

Thus, this study uses multi-criteria decision analysis (MCDA) with spatial solutions in a Geographic Information System (GIS) to conduct LSA. Multi-criteria analysis with GIS has the advantages to support decision-making process by a systematic way and reflect a transparent decision by the use of thematic maps (Ferretti and Pomarico, 2013). This multidisciplinary approach has diverse applications in spatial analysis for land use (Hassan and Nazem 2016; Hossain *et al*., 2009; Ferretti and Pomarico, 2012) and stated as a powerful integrated method for complex land use scenario (Saleh *et al*., 2015). Furthermore, the land suitability analysis has been conducted specially for different agricultural crops, aquaculture, ecotourism, landfill site selection and wind and solar power plants over a period of time (Chandio *et. al.,* 2013). In the recent researches, a macro level based using GIS, Fuzzy Inference Systems (FIS) and AHP. Criteria were evaluated by the FIS and AHP were used for the criteria weights and finally the aggregation was done in MCDA4ArcMap (Rikalovic *et. al*., 2015). However, the system is useful only when the spatial analysis is done on vector-based polygon database. Another study was conducted for the industrial state selection using GIS and AHP and has taken seven criteria for evaluation (Edrahim *et. al.*, 2015). Here, AHP was conducted taking one expertise's evaluation, which had the possibility of having a bias judgment. In addition, the scoring of the individual criterion was not explained properly. Furthermore, Eldin and Sui (2003) used Component Object Model (COM) for designing a decision support system for industrial site selection. They suggested two phases, site screening which was done by the Expert System (ES) and the GIS. In the second phase, AHP was used to evaluate non-spatial criteria. However, a prototype approach was applied as it was unable to deal with complexities of GIS and can deal with a limited range of industrial facilities and criteria. Again, COM Technology were applied for integrating loose coupling and tight coupling for industrial site selection (Eldrandaly *et. al*., 2005). In this research, it was not clear how the criteria were prioritized for the industrial site selection.

Furthermore, there were few attempts were taken to industrial site selection using GIS-based MCDA. The GIS-based MCDA method was described as a procedure that accumulates and transforms spatial and non-spatial data (input) into a resultant decision (Malczewski, 2004). The MCDA method builds a connection between the input map and output map by utilizing geographical data and the judgment values of decision makers according to the facts and correlates the specified decision rules. The MCDA methods can be used in a GIS environment, such as Boolean overlays, Weighted Linear Combinations (WLC), Ordered Weighted Averaging (OWA), the Analytical Hierarchy Process (AHP), and Multiple-objective land allocation (MOLA) (Rikalovic *et al*., 2014). The integration of multi-criteria methods for land suitability analysis with a GIS system has broadened the spatial proficiencies of GIS and explored this system's analytical power as a decision-support tool. This GIS-based decision tools have immense potential to apply in the wide array of regional application to enhance the economic growth with spatial decisions for suitable site section of industrial lands including stakeholders and expert's opinions.

Bangladesh has mixed land use, so including stakeholders and experts' opinions in LSA studies is important. AHP is the most widely used MCDA method and has the flexibility to include experts' decisions. The AHP is a systematic decision-making technique that decomposes the problem into a hierarchy of sub-problems to comprehend and evaluate the problem more easily and subjectively (Saaty, 1980). A numerical scale is used to rank subjective evaluations, which are transformed into numerical values (Bhushan and Rai, 2004). The AHP is also a multiple criteria decision-making tool that accumulates spatial analysis functions of GIS in land suitability analysis to produce suitability maps (Chandio *et al.*, 2011). The LSA is an application-based approach has the opportunity, which could be used for a long run planning for site selection. Considering the above-mentioned research, which had the limitation and required to introduce a model of land suitability analysis for industrial site selection using GIS and AHP. The latitude of flexibility of LSA model must have the applicability for the local level to national level for industrial site selection. The most effective part of the study is that the model efficiently tries to protect the current agricultural lands and considered expert opinions from different fields.

3.2 Objectives

The objective of this part of research was to find out the suitable sites for the industries as economic zones for Bangladesh by protecting the existing agricultural lands. The methodological concept using GIS and MCDA for the land suitability analysis for industrial site selection was first applied to a small scale. In addition, the study aimed to analyze the statistical agricultural data and industrial locations with the help of GIS to know the influence of the existing industrial sites for agricultural land use transformation.

3.3 Materials and Methods

3.3.1 Conceptual Framework

The study was performed in two stages. In the first stage, agricultural land use statistical data was analysed with the help of GIS to know the influence of industrial growth on the agricultural land **(Figure 3.1).** Since the study area had faced rapid transformation of land use in the last three decades, mostly reported for urban and industrial development (Rashid, 2003; Sharif and Esa, 2014). The statistical data of agricultural land was taken from the local agricultural department from 2002 to 2011. The data were analysed and determined the percentage increased/decreased in each small administrative unit of Savar. To visualize the agricultural land status, ArcGIS 10.3® was used and prepared a map. In addition, Garmin eTrex 30 was used to collect the geographical positions of 420 factories during the base line survey in Savar. These factories location were mapped using GIS and overlay with the agricultural land use statistical map.

In the second stage, land suitability analysis was conducted to find out the suitable sites of industries adopting spatial modelling of GIS-MCDA. It was reported that data used by the decision makers and managers were mostly associated with geographical analysis (Worall, 1991). Therefore, the land suitability analysis was conducted in GIS environment integrating AHP as a multi-criteria analysis (MCA) to evaluate and to incorporate the expert's judgements.

Multi approach decision making is now widely used by the researchers, policy makers to solve the real time scenarios. In this study, the MCA was performed with 23 factors and 7 constraints under 9 criteria. Baseline survey, review of literatures and expert's opinions helped to select the criteria. Since geographical decisions mostly related to the local environment and regulations, importance was given to the local stakeholders for finalized the criteria. AHP is considered one of the most useful and widely used multi-criteria analysis to incorporate experts and stakeholder's opinion. Thus, AHP was implemented here to weight the preferences of the criteria.

In the GIS environment, the thematic data set of the selected criteria were analysed by the spatial analyst tools to prepare the factors and constraints layers. The factors and constraints layers were further reclassified according to the score given to each factors and constraints. Finally, a decision rule was employed to aggregate the scores of factors and constraints of each criterion and the weights of each criteria taken from AHP technique.

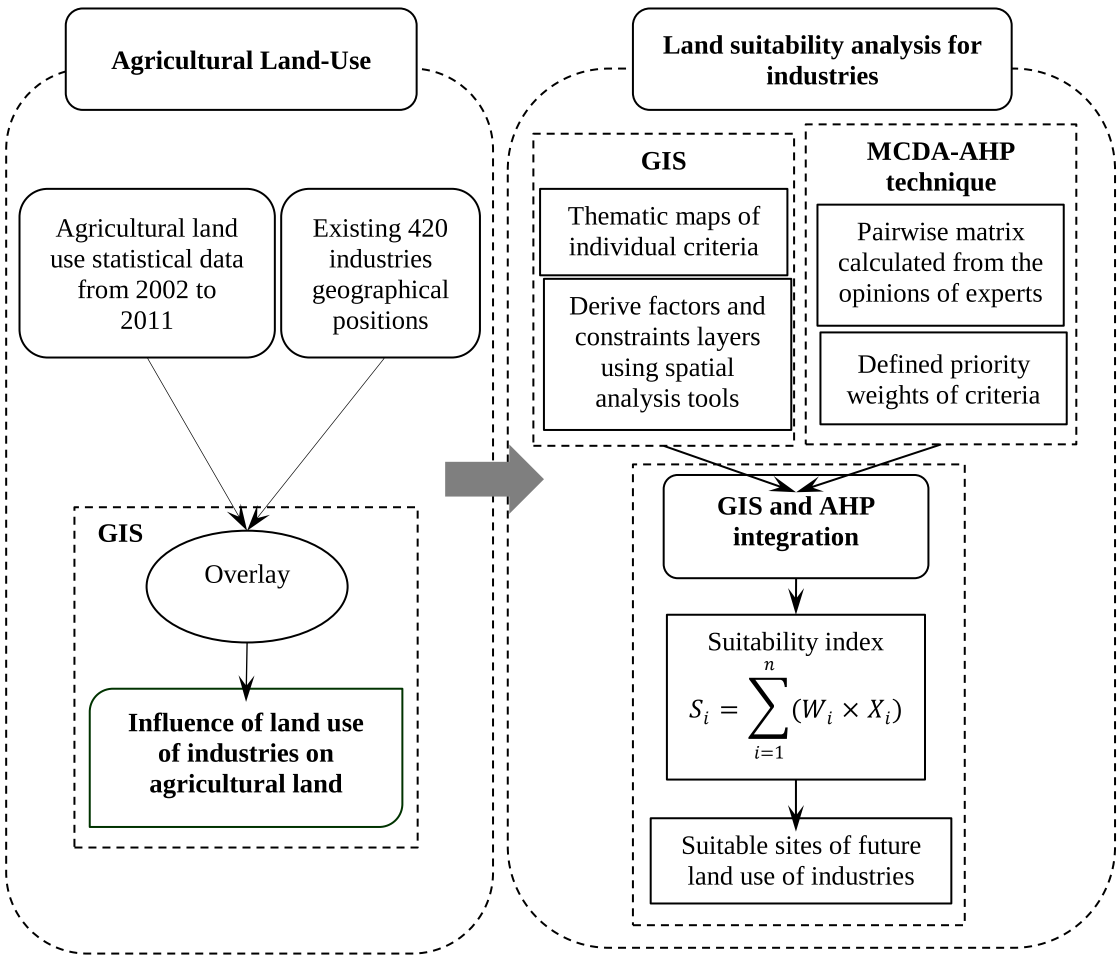


Figure 3.1 Framework for industrial site selection and influence on the agricultural land use.

3.3.2 MCA Procedure for LSA

A multi dimension aspects are involved in land suitability analysis, especially when implemented for facility site selection. Environmental regulations, social obligatory, economy of the inhabitants, land use and land cover and hazards and disasters risk of the sites are the most curial aspects to consider while performing the land suitability analysis. Furthermore, land resources are mostly handle by the local legislation and stakeholders which is more complicated especially in the developing countries. In addition, the availability of land is essential for site selection. Thus, a most updated spatial datasets are the prime requirement for conducting land suitability analysis. The land suitability analysis become together while conducting the study in a heterogeneous land use with densely populated area.

On this scenario, the multi-criteria analysis was the best approach to deal with a number of domains in spatial environment. The study followed a chronological order to conduct the MCA analysis **(Figure 3.2)**. In the research, nine criteria were selected to conduct MCA, to achieve the research goal and objectives. Beinat (1998) defined a criterion as a basis for decisions that can be measured and evaluated. In selecting criteria for the locations of industries, Eugene and Prasanta (2005) stated that environmental and social factors are the most important aspects for the sustainable development of industries. Ensuring these that these conditions are met during site selection help to maintain a high level of productivity throughout the lifetimes of projects. Thus, the criteria were selected for this part of this research focused primarily on environmental and social aspects.

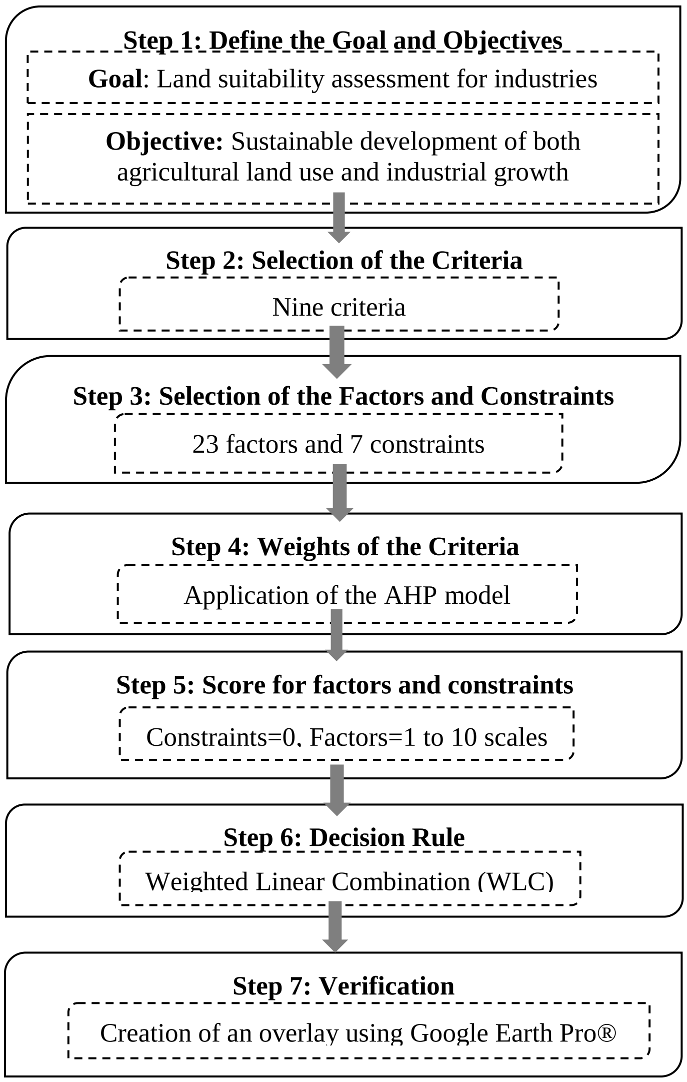


Figure 3.2 Multi-criteria analysis for determining land suitability.

The criteria used in this study were the proximity to 1) major roads and 2) local roads; the distance from 3) rivers, 4) water bodies, 5) settlements, and 6) agricultural lands; 7) the presence of flood flow zones; 8) slope; and 9) elevation. These criteria were further classified into factors and constraints for assessment. According to Beinat (1998), a factor is a criterion that enhances or detracts from suitable alternatives for the activity under consideration, and a constraint serves to limit any alternatives. This study focused on 23 factors and 7 constraints based on these definitions. Furthermore, expert opinions were obtained using a questionnaire designed for use with the AHP technique to evaluate the priority weights of the criteria. A score was assigned to each factor on a scale of 1-10, and the constraints were stated as "restrictions". To aggregate the weights of the criteria and the scores of the corresponding factors and constraints under each criterion, a decision rule called weighted linear combinations (WLC) was applied to determine suitable locations for industrial sites. The resulting map was further analysed to distinguish compact parcels that could be suggested for development as industrial zones. The final result was then displayed in Google Earth Pro® to evaluate the results.

3.3.3 Study Area

The study was conducted in Savar 25 km from the capital city of Dhaka. Savar is a part of RAJUK (Rajdhani Unnayan Kartripakkha), the Capital Development Authority of the Government of Bangladesh. According to data covering the Savar Agricultural Department in 2011, 63.75% of the area of Savar was made up of agricultural lands. The interface between rural and urban areas is significant in the northwestern and southeastern areas of Savar. Savar is located between the latitudes of 23°44'15.51"N and 24°1'29.19"N and between the longitudes of 90°11'22.78"E and 90°21'31.17"E (degrees-minutes-seconds, WGS84). The total area of Savar is 280.13 km^2, and its neighboring sub-districts are Kaliakair and Gazipur Sadar to the north; Keraniganj to the south; Mirpur, Mohammadpur, Pallabi and Uttara Thanas of the Dhaka City Corporation to the east; and the Dhamrai and Singair sub-districts to the west **(Figure 3.3).** The land height gradually increases from east to west, and the area is bounded by the Bangshi, Turag, Buriganga and Karnatali rivers. The population density of Savar was 4,948 per km^2 in 2011, an increase of 8.84% per year from the previous census in 2001. Approximately 78.6% of the population was distributed within rural areas, whereas the rest lived in urban areas (BBS, 2011).

The study area contains several types of landscapes, including highlands, moderate highlands, and lands of moderate elevation, lowlands and very low lands, based on their drainage, elevation and pedological properties (Rashid, 2003). The highlands do not flood and are mostly used for growing vegetables throughout the year. These lands are relatively less productive for rice. The highlands are the most suitable areas for the development of permanent infrastructure. The lands of moderate elevation are used for single crops, such as high-yielding variety (HYV) rice and Boro rice because these areas are fertile lands. The lowlands and very low lands are very suitable for agricultural purposes because these lands receive prolonged flood waters from the Dhaleshwari, Bansi and Turag Rivers.

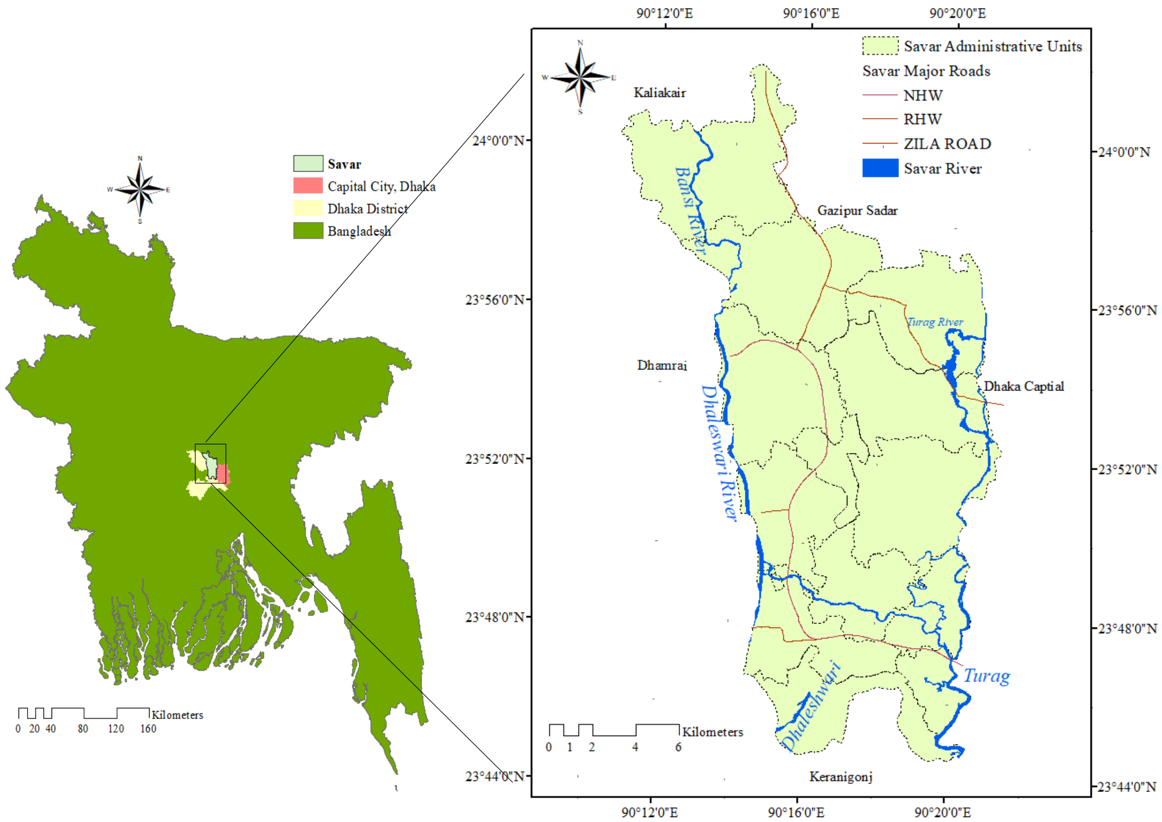


Figure 3.3 Location map of the study area (modified from LGED base maps).

According to the data from 2011-2012 from the Savar Agricultural Office, Savar produces rice (Boro, T-aman, and Aus), wheat, maize, mustard, nuts, pulses, vegetables, fruits, and spices. According to employment data covering Savar, 14.54%, 42.57%, and 42.89% of the population was engaged in agriculture, industry and the service sector, respectively (BBS, 2011). The agricultural industries found in Savar include combined fisheries, dairies, poultries, and hatcheries. On the other hand, Savar is mostly known as an industrial hub, due to the number of industries that manufacture products such as ceramics, beverages, garments, footwear, jute, textiles, automobiles, pharmaceuticals, and bricks. The second largest export processing zone (EPZ) in Bangladesh, the Dhaka EPZ, was established in Savar in 1993.

3.3.4 Data and Thematic Maps

The focus of this section of research was to assess agricultural land use change in an area well known for industries and to perform a land suitability analysis suitable for industries. The statistical data of agricultural lands were analyzed. The data of agricultural land use and primary data of the geographical locations of cloth industries **(Table 3.1)** was used in the analysis with the application of GIS. Next the GIS analysis was conducted to know whether Savar had any suitable place that have the potential to expand more industries by protecting current agricultural lands. GIS and AHP, a technique of multi-criteria analysis was integrated to conduct the research. The analysis was done by a set of collected feature maps **(Table 3.2)** and the judgement of expert.

A field survey was done after the preliminary study. During the field survey, secondary data of the agricultural land use were collected from the Local Government Agricultural Office. In addition, the addresses of the cloth factories were taken from the Bangladesh Garment Manufactures and Exporters Association (BGMEA). This secondary data was used to collect the primary data of the geographical positions (Longitudes and Latitudes) of 420 cloth factories, spread throughout in the Savar areas. Global Positioning System (GPS) receiver device (Garmin etrex 30) was to get the waypoints of these industries in the map. Furthermore, interviews were conducted to the concern persons related to cloth industries to know the criteria for suitable locations of factories. All the feature maps **(Figure 3.3, 3.4, 3.5 and 3.6)** of Savar, such as major roads, local roads, rivers, water bodies and settlements, used in the analysis were collected by the collaboration with Local Government Engineering Department (LGED). In addition, agricultural land use map and flood flow zones were collected from the Capital Development Authority, Rajdhani Unnayan Kartripakkha (RAJUK).

Table 3.1 List of statistical databases including factories, and agricultural land use.

No.	Data	Source	Date Collected	Data Type
1	Savar cloth factories data, 2013	BGMEA (Bangladesh Garment Manufactures & Exporters Association)	2013	Secondary data
2	Geographical location of the cloth factories	Field survey (by GARMIN-eTrex 30, GPS device)	Sep, 2013	Primary data
3	Agricultural land use data, 2002	Local Agricultural Office, Savar	August, 2013	Secondary data
4	Agricultural land use data, 2011	Local Agricultural Office, Savar	August, 2013	Secondary data

Table 3.2 List of feature's maps used to analyze in GIS.

No.	MAPS	Source	Scale
1	Savar administrative boundary map, 2010	LGED, Bangladesh (Local Government Engineering Department)	1:50000
2	Savar main roads map, 2013	LGED, Bangladesh	1:50000
3	Savar local roads map, 2013	LGED, Bangladesh	1:50000
4	Savar settlement boundary map, 2010	LGED, Bangladesh	1:50000
5	Savar rivers map, 2010	LGED, Bangladesh	1:50000
6	Savar water bodies map, 2010	LGED, Bangladesh	1:50000
7	Savar agricultural land map, 2013	RAJUK, Bangladesh	1:50000
8	Savar flood zone map, 2013	RAJUK, Bangladesh	1:50000
9	Savar satellite image, 2015	Google Earth Pro®	4800x2718 Pixel

3.3.5 Field Survey

Statistical data describing the extent of agricultural land in 2002 and 2011 were collected from the local agricultural office during a field survey in Savar. A list of cloth-producing industries in Savar was obtained from the Bangladesh Garment Manufacturers & Exporters Association (BGMEA). Nine criteria were selected based on field observations and discussions with stakeholders. A questionnaire based on the AHP method was used to record the opinions of experts in terms of pairwise comparisons of criteria. In addition, spatial maps of the geographic features relevant to the criteria were obtained from different organizations for GIS analysis **(Table 3.3).**

Table 3.3 List of feature maps that were analysed in GIS.

No.	Map	Source	Scale
1	Savar Administrative Boundary Map, 2010	LGED*, Bangladesh	1:50000
2	Savar Main Roads Map, 2013	LGED, Bangladesh	1:50000
2	Savar Local Roads Map, 2013	LGED, Bangladesh	1:50000
3	Savar Settlement Boundary Map, 2010	LGED, Bangladesh	1:50000
4	Savar Rivers Map, 2010	LGED, Bangladesh	1:50000
5	Savar Water Bodies Map, 2010	LGED, Bangladesh	1:50000
6	Savar Agricultural Land Map, 2013	RAJUK*, Bangladesh	1:50000
7	Savar Flood Zone Map, 2013	RAJUK, Bangladesh	1:50000
8	Digital Elevation Model (DEM)	Shuttle Radar Topography Mission (SRTM)	1 arc-second for global coverage (~30 m)

*LGED-Local Government Engineering Department, RAJUK-Capital Development Authority, Rajdhani Unnayan Kartripakkha

3.3.6 Criteria, Factors and Constraints

One of the major steps in locating suitable sites is to identify a set of dominant factors that are applicable to site selection (Rikalovic *et. al*., 2014). Thus, the combination of knowledge from local stakeholders, discussion with experts, field observations and previous studies can be applied to select and score the factors, constraints, and criteria **(Table 3.4).**

Table 3.4 Scores and suitability classifications of the factors and constraints.

No.	Name of Criterion	Factor/ Constraint	Classification	Score*	Suitability
1	Proximity to major roads	0-100 m	Constraint	0	Not suitable
		100-500 m	Factor	10	Most suitable
		500-1000 m	Factor	8	Moderately suitable
		1000-1500 m	Factor	6	Less suitable
		1500-2000 m	Factor	4	Least suitable
		>2000 m	Factor	2	Suitable but avoided
2	Proximity to local roads	0-50 m	Constraint	0	Not suitable
		50-200 m	Factor	10	Most suitable
		200-400 m	Factor	6	Less suitable
		>400 m	Factor	2	Suitable but avoided
3	Distance from rivers	0-500 m	Constraint	0	Not suitable
		500-750 m	Factor	4	Least suitable
		750-1000 m	Factor	8	Moderately suitable
		>1000 m	Factor	10	Most suitable
4	Distance from water bodies	0-100 m	Constraint	0	Not suitable
		>100	Factor	10	Most suitable
5	Distance from settlements	0-50 m	Constraint	0	Not suitable
		>50 m	Factor	10	Most suitable
6	Flood flow zones	Flood flow zone	Factor	2	Suitable but avoided
		Non-flood flow zone	Factor	10	Most suitable
7	Distance from agricultural lands	0-50 m	Factor	2	Suitable but avoided
		>50 m	Factor	10	Most suitable
8	Slope	0-5%	Factor	10	Most suitable
		6-10%	Factor	8	Moderately suitable
		11-15%	Factor	6	Less suitable
		>15%	Constraint	0	Not suitable
9	Elevation	0-5 m	Constraint	0	Not suitable
		6-10 m	Factor	6	Less suitable
		11-15 m	Factor	8	Moderately suitable
		>15 m	Factor	10	Most suitable

***** Scores are based on field observations, discussion with experts and previous studies.

3.3.6.1 Proximity to major roads

Access to roads is the most important criterion when selecting a factory site. Imports of raw materials and exports of the final goods are conducted though the main port. National highways, regional highways and district roads are the main routes to the port of Chittagong in Chittagong city. Chittagong is located 308 km away from Savar in the southeastern part of the country, and it is the second largest city in Bangladesh. The national highway N1 (the Dhaka-Chittagong national route) connects the two largest cities in Bangladesh and is 250 km long; approximately 7 to 8 hours of travel time are required to traverse this road. Emphasizing the efficiency of the road communication network, as of 2016, the N1 national highway has 4 lanes to reduce the travel time. Thus, assessing the distances from the factories to the national highway is very important. An increase in distance results in higher transportation costs and production lead time. The closer a factory is to the national highway, the lower the transportation costs and production lead time are. In addition, buffer zones were constructed with different widths, considering the existing distribution of factories, which are mostly located near the local and major roads. Distances of 100-500 m were assigned a score of "10" to indicate "most suitable"; distances of 500-1000 m were assigned a score of "8" to indicate "moderately suitable"; distances of 1000-1500 m were assigned a score of "6" to indicate "less suitable"; distances of 1500-2000 m were assigned a score of "4" to indicate "least suitable"; and distances greater than 2000 m were assigned a score of "2" to indicate "suitable but avoided". However, buffer zones with a width of 100 m were established that are not suitable for any industrial site to maintain a safe distance from major roads; thus, the 100-m buffer area around major roads were considered as constraints of the criterion and assigned a score of "0", i.e., "not suitable" (Anurag, 2010).

3.3.6.2 Proximity to local roads

Most of the factories were connected to major roads via local roads. Therefore, buffer zones with widths of 50-200 m around these roads were assigned a score of "10" to indicate "most suitable"; buffer zones with widths of 200-400 m were assigned a score of "6" to indicate "less suitable"; and areas that lay more than 400 m from local roads were assigned a score of "2" to indicate "suitable but avoided". A 50-m buffer zone around local road was taken as a constraint and assigned a score of "0", i.e., "not suitable", to indicate that industrial operations should maintain a safe distance from roads (Anurag, 2010).

3.3.6.3. Distance from rivers

The study area is surrounded by rivers. Considering the environmental aspects, hazards, and risks, the “most suitable” industrial sites were considered to be 1000 m from the rivers, which were assigned a score of “10”. In addition, a 500-m buffer zone around the rivers was considered “not suitable” for any industrial site. This requirement was considered a constraint, and these areas were assigned a score of “0”. Beyond this constraint, the 500-750-m buffer zone was assigned a score of “4”, i.e., “least suitable”, and the 750-1000-m zone was assigned a score of “8”, i.e., “moderately suitable”.

3.3.6.4 Distance from water bodies

Water bodies are also a concern because of environmental hazard issues. Industrial wastewater and solid waste can affect water bodies and the agricultural lands. Thus, a 100-m buffer zone around water bodies was treated as a restriction, i.e., “not suitable”, and assigned a score of “0”. Areas beyond this restriction zone were considered “most suitable” and scored “10”.

3.3.6.5 Distance from settlements

Settlements were the most significant criteria. The rapid transformation of land use and the growth of urbanization and industrialization have resulted in a complex distribution of land cover types within Savar. Industries are scattered from city areas to suburban areas and influence rural settlements. However, industrial sites must maintain a certain distance from the settlements to prevent environmental hazards. Engene and Prasanta (2005) suggested a 100-m buffer between residential areas and limestone quarry operations for use in the cement industry. However, the current study focuses on searching for suitable sites for compact zones that will be separated from other urban settlements. Considering the vacant land crisis in Bangladesh, 50-m buffer zones around settlement areas were assigned a score of “0” for “not suitable”. Other locations were considered “most suitable” and assigned a score of “10”.

3.3.6.6 Flood flow zone

Flood flow zones are mostly located in the eastern and western parts of Savar. Floods occur primarily during the monsoon season. Once the flood waters begin to decline, the land becomes usable for agriculture. Thus, flood flow zones were assigned a score of “2” for "suitable but avoided", and non-flood zones were considered the "most suitable" places under this criterion and assigned a score of "10".

3.3.6.7 Distance from agricultural lands

The agricultural lands are located mostly in the central portion of Savar. As mentioned above, the areas that experience flood risks are also used for agricultural purposes after the water level declines. In Bangladesh, agricultural lands are mostly owned by small-scale farmers; thus, it is comparatively inexpensive and easy to convert land to non-agricultural purposes. Studies have also found that the land ownership size of a household and the non-agricultural occupation of heads of households were the two primary reasons for agricultural land transformation, resulting in declines in agrarian income and productivity (Quasem, 2011). On the other hand, the existing land use policies, the 1950 State Acquisition and Tenancy Act and the 2001 National Land Use Policy of Bangladesh, have seen little implementation and have had relatively small effects (Alam *et. al.,* 2016). Although these historical land policies emphasize the conservation of agricultural lands and limit their transformation to non-farming purposes, they leave room for flexibility, which has caused the policies to be ineffective (LANDac, 2012). The most recent initiative from the Ministry of Land is a draft of the 'Agricultural Land Protection and Land Use Act of 2015', which will soon be finalized (Karim 2015). However, existing policies indicate that agricultural lands should not be used for non-agricultural purposes. Thus, a buffer zone of 50 m around the agricultural lands was considered as "suitable but avoided" and assigned a score of "2", and areas beyond 50 m were taken to be "most suitable".

3.3.6.8 Slope

Higher slopes increase the cost of constructing a facility and the inconvenience of the transportation of goods. The study area contains no steep slopes; however, slope is considered to be a basic criterion for LSA. Thus, areas with slopes of 0-5% were considered "most suitable" and were assigned scores of "10", and areas with slopes of 6-10%, 11-15% and greater than 15% were considered to be "moderately suitable", "less suitable" and "not suitable" and were assigned scores of "8", "6" and "0", respectively.

3.3.6.9 Elevation

Elevation is another important criterion for any industrial site. Highlands are always the first choice for infrastructure projects. The elevation of the central administrative area of Savar is 15 m. However, flood zones also exist in the eastern and western areas. Thus, areas with elevations greater than 15 m were considered to be "most suitable" and were assigned a score of "10"; areas with elevations of 11-15 m were assigned a score of "8", i.e., "moderately suitable"; areas with elevations of 6-10 m were considered "less suitable" and were assigned a score of "6"; and areas with elevations less than 5 m were taken as a constraint and assigned a score of "0".

3.3.7 AHP

The most difficult task in carrying out the LSA approach for a particular land use type is to assign the relative weights of the individual criteria that are to be used. The AHP technique allows the calculation and evaluation of relative weights (Duc, 2006). In addition, one of the most important benefits of using the AHP is that experts from different backgrounds can provide their opinions, thus helping to evaluate the diverse dimensions of the problem being considered (Oguztimur, 2011). However, many studies have questioned the validity of the AHP; in particular, Belton and Gear (Belton and Gear 1982) first noted the phenomenon of rank reversal. Rank reversal occurs when adding or removing an alternative to the AHP changes the relative rankings of the existing alternatives. To address this rank reversal problem, studies and discussions have been conducted, and new mathematical approaches have been introduced (Shin *et. al*., 2013; Wang and Elhag, 2006). On the other hand, the legitimacy of rank reversal has also been debated (Saaty, 1984; Saaty, 1987). In addition, researchers have also proven that rank reversal also appears in other multi-criteria decision making (MCDM) approaches, such as the Borda-Kendall (BK) method, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method and the simple additive weighting (SAW) method (Shin *et. al.*, 2013; Wang, 2009). Nevertheless, researchers believe that the AHP is practiced outside of academia and that the use of AHP in the real world will be continued by its practitioners (Ishizaka and Labib, 2011; Chandio *et. al.,* 2013).

Following the successful applications of the AHP in LSA, this study applied the technique to prioritize the weights of the criteria. A questionnaire was designed according to the AHP model to enable pairwise comparison of each criterion with another criterion based on a nine-point scale **(Table 3.5).** Saaty (1990) stated that the number of elements for the comparison must be less than or equal to 9 to ensure consistency and the corresponding accuracy of the measurements. Saaty (1987) also noted that, if the number of elements is large, then their relative priorities will be small; in such cases, the judgments of the queried experts may contain errors. Thus, the study limited the criteria to the 9 most important aspects.

Table 3.5 Nine-point scale (Satty, 1990).

Intensity of importance on an absolute scale	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favour one activity over another
7	Very strong importance	An activity is strongly favoured, and its dominance is demonstrated in practice
9	Extreme importance	Evidence that favour one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgments	When compromise is needed
Reciprocals	If activity *i* is assigned one of the above numbers compared to activity *j*, then *j* has the reciprocal value compared to *i*	
Rational	Ratios that arise from the scale	If consistency were to be forced by obtaining *n* numerical values to span the matrix

The judgments of the experts were used to prepare a pairwise matrix, and normalization was then performed. That is, the columns in the matrix were summed individually, and then each cell in the column was divided by the sum of the corresponding column. The column sum of the resultant matrix was equal to 1. The pairwise matrix can be expressed as follows:

$$\begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \tag{3.1}$$

where C_{11} is the value of row i (the 1st row) and column j (the 1st column) in the pairwise comparison matrix. The column sum of the pairwise matrix can be expressed as follows:

$$C_{ij} = \sum_{i=1}^{n} C_{ij} \tag{3.2}$$

Therefore, the normalization for each column value can be expressed using the following equations:

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} = \begin{bmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ X_{31} & X_{32} & X_{33} \end{bmatrix} \tag{3.3}$$

After normalization, the row sum in the new matrix was divided by the total number of criteria. This process and the resulting vector of weights can be expressed as follows:

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} = \begin{bmatrix} W_{11} \\ W_{12} \\ W_{13} \end{bmatrix} \tag{3.4}$$

This matrix of weights can only be used after calculating the consistency ratio (CR), as it evaluates the credibility of the judgments of the individual respondents. The pairwise matrices are considered to be consistent when the CR is less than 0.1 (10%). The pairwise matrices are considered to be inconsistent, and the resultant weight matrix of the criteria is not acceptable, when the CR is greater than 0.1 (Saaty, 1980).

The initial consistency vectors were derived by multiplying the pairwise matrix by the vector of weights:

$$\begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} * \begin{bmatrix} W_{11} \\ W_{12} \\ W_{13} \end{bmatrix} = \begin{bmatrix} C_{11}W_{11} + C_{12}W_{21} + C_{13}W_{31} \\ C_{21}W_{11} + C_{22}W_{21} + C_{23}W_{31} \\ C_{31}W_{11} + C_{32}W_{21} + C_{33}W_{31} \end{bmatrix} \tag{3.5}$$

The principal eigenvector (λ_{max}) was then calculated by averaging the values of the consistency vector:

$$\lambda_{max} = \sum_{i}^{n} CV_{ij} \tag{3.6}$$

The consistency index (CI) was calculated as:

$$\text{CI} = \frac{\lambda_{max} - n}{n - 1} \tag{3.7}$$

Here, *n* is the total number of criteria. The consistency ratio was calculated as:

$$\text{CR} = \frac{CI}{RI} \tag{3.8}$$

where *RI* is the random index from **Table 3.6**.

Table 3.6 Random inconsistency indices for *n=10* (Saaty, 1987).

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Random inconsistency index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

3.3.8 GIS Application for LSA

The GIS analysis was designed to be conducted in ArcGIS 10.3® using vector and raster layers. Initially, seven thematic vector layers that represent the major roads, local roads, rivers, water bodies, settlements, flood flow zones, and agricultural lands were expressed in a base geographical coordinate system, WGS 1984. These vector layers were then projected into WGS 1984 UTM Zone 45N to obtain the same geographic extent. The thematic layers were then converted to raster layers to conduct the spatial analysis. Here, the polyline feature layers representing major roads and local roads were converted to raster layers using the "Polyline to Raster" conversion tool. The polygon feature layers representing rivers and water bodies were then converted to raster layers using the "Polygon to Raster" conversion tool, and the three remaining polygon layers, which included settlements, flood flow zones and agricultural lands, were converted using the "Feature to Raster" tool **(Figure 3.4).**

A DEM of the study area with a resolution of 30 m was extracted from the SRTM data set. However, before the extraction was performed, the "Mosaic" spatial analysis tool was used to obtain a seamless dataset from the two tiles of the SRTM data that cover the study area. The slope layer was obtained from the DEM using the "Slope" spatial analysis tool. The results were expressed as percentages and classified according to the factors and constraint intervals. The SRTM elevation map was also used as a reference layer to synchronize the raster layers in terms of cell size and processing extent. Thus, the rasterized thematic layers were assigned a cell size of 30 x 30 m.

The “Euclidean distance” spatial analysis tool was used to determine the proximity to major and local roads and the distances from rivers, water bodies and settlements. The Euclidean distance tool measures the distance from each cell to the closest feature of a given type.

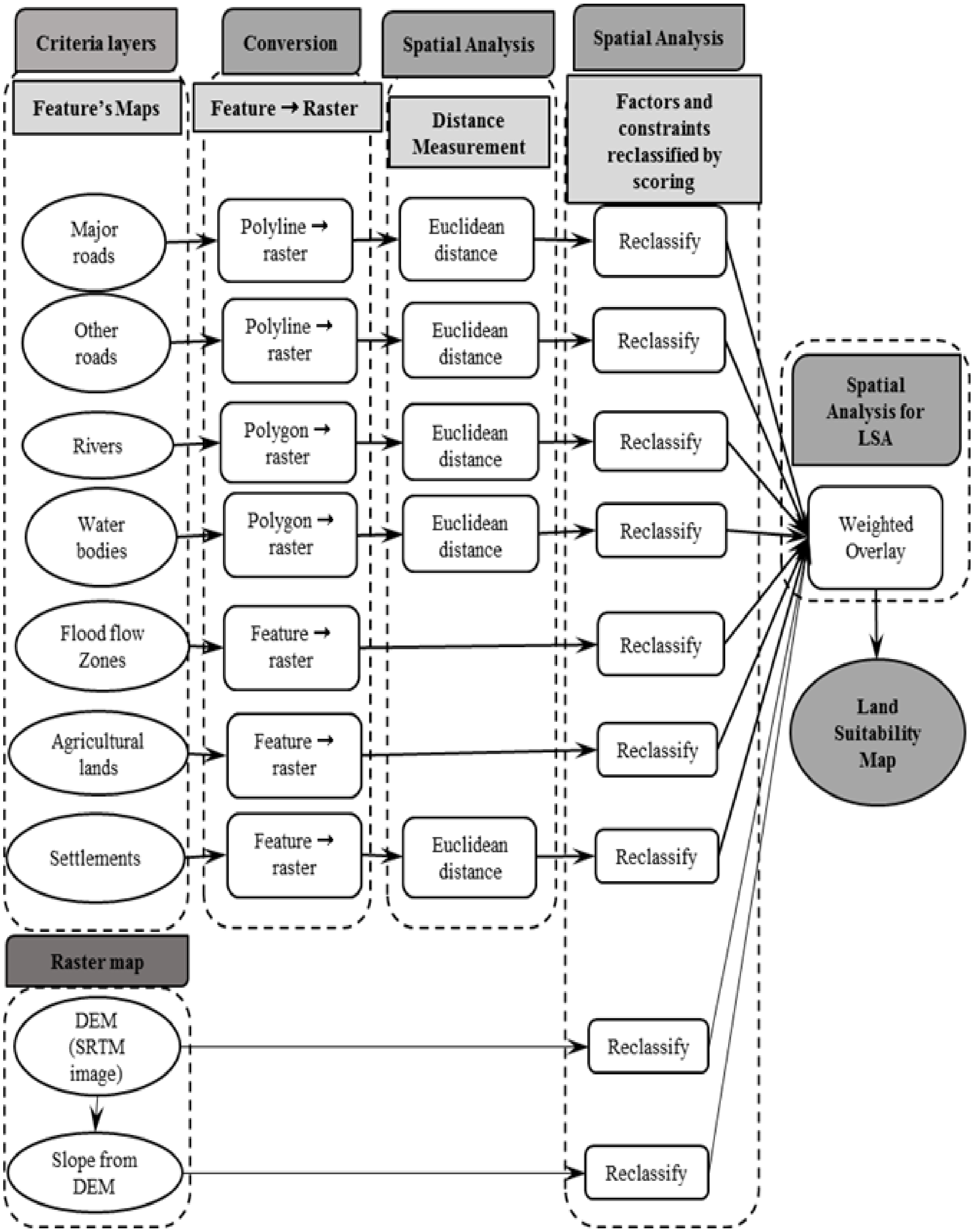


Figure 3.4 Model diagram for the land suitability analysis.

Further, the distance ranges were classified according to the factors and constraints of each criterion.

Further, the "Reclassify" tool was applied to the raster layers using the score rankings of the factors and constraints. Here, the constraints were given the number "1", and the factors were assigned using numerical values ranging from "2" according to the ranking order of their scores. Output raster layers associated with the individual criteria were generated that show the suitability ranking as a colour gradient.

3.3.9 Suitability of Land for Industrial Development

To aggregate the factors and constraints with the weights of the criteria, the "Weighted Overlay" spatial analysis tool was used. This tool worked as a decision rule to integrate the AHP and GIS for the LSA. The weighted–overlay procedure followed the principle of weighted linear combinations (WLC), in which the weights of the criteria are combined with the scores of the factors and constraints to produce a suitability index for each cell of the output map (Eastman *et. al.*, 1995). The following expression describes the suitability index:

$$S_i = \sum_{i=1}^{n} (W_i \times X_i) \tag{3.9}$$

Here, W_i is the weight of each criterion i, which is calculated from the AHP technique of the MCDA, and X_i is the score of each factor and constraint. The scale was set to 1 to 10 within the "Weighted Overlay" tool. The constraints, which were given a ranking of "1" in the reclassification stage, were stated as "restrictions" while applying the "Weighted Overlay" function. The factors were assigned scores between 1 and 10 according to Table 2. The resulting map indicated the suitability of land for industrial development. On this map, each cell of the raster layer was assigned a suitability index on a 0-10 scale, where "0" was assigned to the restricted cells. The map was further classified into four clusters, which were assigned scores of "0" ("not suitable"), "1-5" ("less suitable"), "5-7" ("moderately suitable"), and "8-10" ("most suitable").

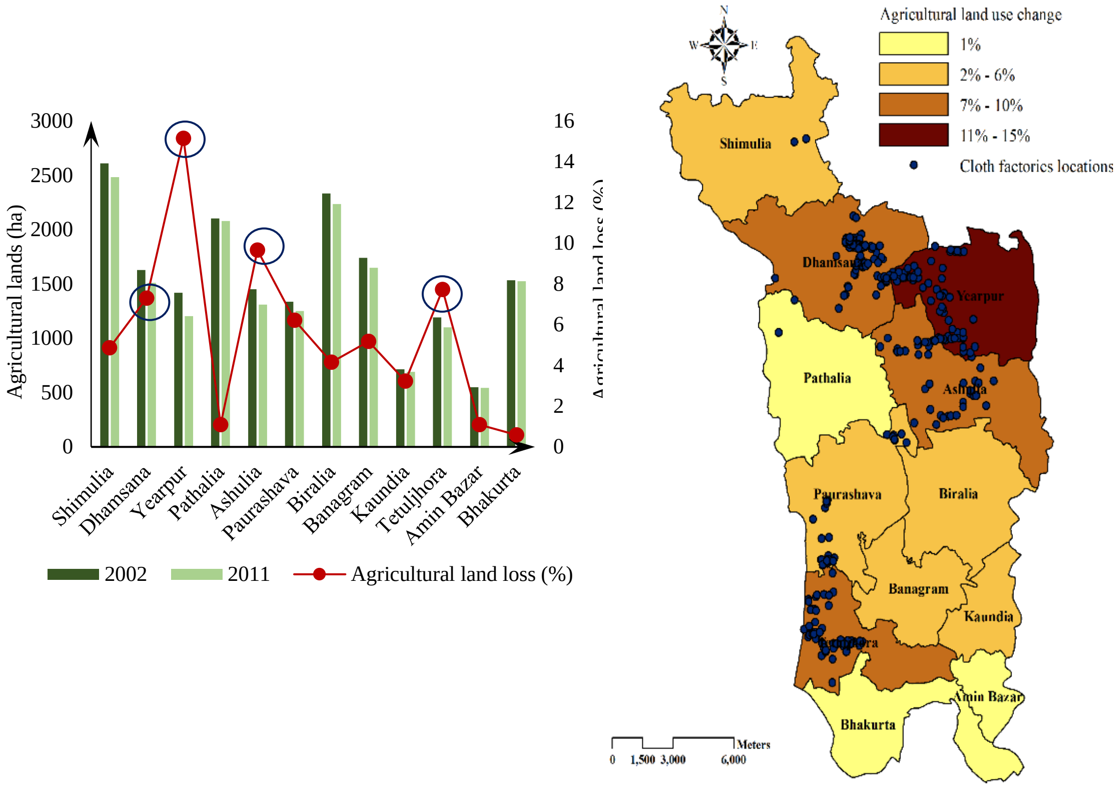
3.3.10 Industrial Zone Selection

Once the LSA had been performed for the industrial sites, GIS was further utilized to select compact areas for industrial zones. The "Set Null" spatial analysis tool was used to identify the "most suitable" cells. An SQL expression was written to identify cells with values less than 8; i.e., cells with values between 8 and 10 would be the true values of the most suitable places. Further, the raster layer was converted from a raster to a feature using the "raster to polygon" conversion tool. The raster cells for the "most suitable" areas were transformed into individual polygons, and the areas of each polygon were calculated. The "select" spatial analysis tool was applied to the feature classes to find polygons covering the most suitable places that contained at least 10 ha of land to build industrial zones. The SQL was set to a value that was less than or equal to 100,000 m^2.

3.4 Results

3.4.1 Agricultural Land Use Changes vs. Industrial Growth

The statistical data from the local agricultural office showed that Savar lost an average of 6% of its agricultural lands from 2002 to 2011 from each administrative unit. In total, 1,064 ha of agricultural land was lost from 2002 to 2011. However, four administrative units in Savar, namely "Yearpur", "Ashulia", "Tetuljhora" and "Dhamsona", exhibited greater losses of agricultural land, 15%, 9%, 8%, and 7%, respectively **(Figure 3.5a).** A visual representation of the agricultural land use changes was produced using GIS, where the colour gradient shows the locations of the highest agricultural land losses **(Figure 3.5b).** According to the BGMEA database of 2013, approximately 577 cloth factories are located in Savar and were scattered among the urban, suburban and rural areas. The study succeeded in collecting the geographical locations of 420 factories during the field survey, and these locations were mapped using GIS. The map shows that the factory locations were most densely clustered in areas where the agricultural land decreased the most from 2002 to 2011 **(Figure 3.5b).**



(a) (b)

Figure 3.5 (a) Statistical representation of agricultural land use changes in 2002 and 2011(Source: Savar Agricultural Office, 2014); (b) interpretation of the agricultural land use changes in GIS.

3.4.2 Expert Judgment

An AHP-based pairwise matrix was developed from the responses of the experts. After normalizing the matrix, the weights of each criterion were calculated based on the judgment of individual experts, followed by the consistency measures, consistency indices and CR values. The CR values of the judgments of the five experts were less than 0.1; i.e., the judgments for the pairwise comparisons proved to be consistent. The average weight for each criterion derived using the individual judgments was used for the LSA. Based on these judgments, the highest priority was given to proximity to major roads (22%), followed by proximity to local roads (14%), elevation (14%), and distance from agricultural lands (13%) **(Table 3.7).**

Table 3.7 The judgments of experts in prioritizing the weights of the different criteria (A, author; B-E, experts from different fields).

Criteria	**A**	**B**	**C**	**D**	**E**	Mean
Proximity to major roads	0.23	0.30	0.09	0.26	0.25	0.22
Proximity to local roads	0.18	0.19	0.08	0.18	0.06	0.14
Distance from rivers	0.07	0.02	0.09	0.07	0.10	0.07
Distance from water bodies	0.11	0.06	0.11	0.06	0.06	0.08
Distance from settlements	0.09	0.10	0.14	0.05	0.05	0.09
Distance from flood flow zones	0.05	0.06	0.15	0.05	0.06	0.08
Distance from agricultural lands	0.11	0.15	0.24	0.14	0.03	0.13
Slope	0.04	0.03	0.06	0.02	0.11	0.05
Elevation	0.13	0.09	0.06	0.17	0.28	0.14
CR	**0.08**	**0.06**	**0.06**	**0.09**	**0.09**	

3.4.3 GIS Spatial Analysis

The "Reclassify" tool in ArcGIS® was used to categorize Savar area based on the ranking order of the factors and the constraints associated with each criterion. The first map **(Figure 3.6a)** shows the proximity to major roads, for which 13% of the area was found to be "most suitable", reflecting areas located between 100 m and 500 m from the major roads. Based on this criterion, the moderately suitable, less suitable and least suitable areas were found, and these zones corresponded to 15%, 13% and 12% of the total area, respectively. However, the largest fraction of the area, i.e., 44%, was assigned to zones that are "suitable but avoided". The proximity to major roads was selected as the first priority in the LSA of industries by the experts. Therefore, given that only 13% of the corresponds areas are most suitable for industrial development, in terms of their proximity to major roads, limited the possibility of obtaining considerable land areas for industries. The map resulting from application of the second-highest-priority criterion, proximity to local roads, found that 15% of land in Savar was "most suitable", followed by 19% that was "less suitable" and 6% that was "not suitable". 60% of the land area was reported as "suitable but avoided" **(Figure 3.6b).**

Approximately 54% of area in Savar was located more than 1000 m away from rivers and was therefore "most suitable". Because most of the rivers are located along the administrative boundaries of Savar, only 29% was found to be "not suitable" **(Figure 3.6c).** In addition, due to the small number of water bodies, 95% of area was found to be more than 100 m from them and was therefore classified as "most suitable" **(Figure 3.6d).**

Settlements were an important determinant of the available areas. Fifty-four percent of the land was located 50 m away from the settlements and was therefore "most suitable" **(Figure 3.6e).** To identify the hazard-free lands, 22% of area was found to lie within flood zones, whereas the remainder (78%) was found to be "most suitable" **(Figure 3.6f).**

In addition, the spatial analysis found that 69% of area lay at least 50 m from agricultural lands and was therefore "most suitable". On the other hand, the remainder (31%) lay within 50 m of agricultural lands **(Figure 3.6g).** This result played an important role in determining the final outcome of the LSA because this research was intended to preserve the existing agricultural lands.

Furthermore, under the slope criterion, 66% of Savar's area was found to be "most suitable", and 29% of area was found to be "moderately suitable" **(Figure 3.6h).** On the other hand, based on elevation, 19% of area was found to have an elevation greater than 15 m, corresponding to the "most suitable" category **(Figure 3.6g).** The details of the land suitability classification based on the individual criteria are given in **Table 3.8.**

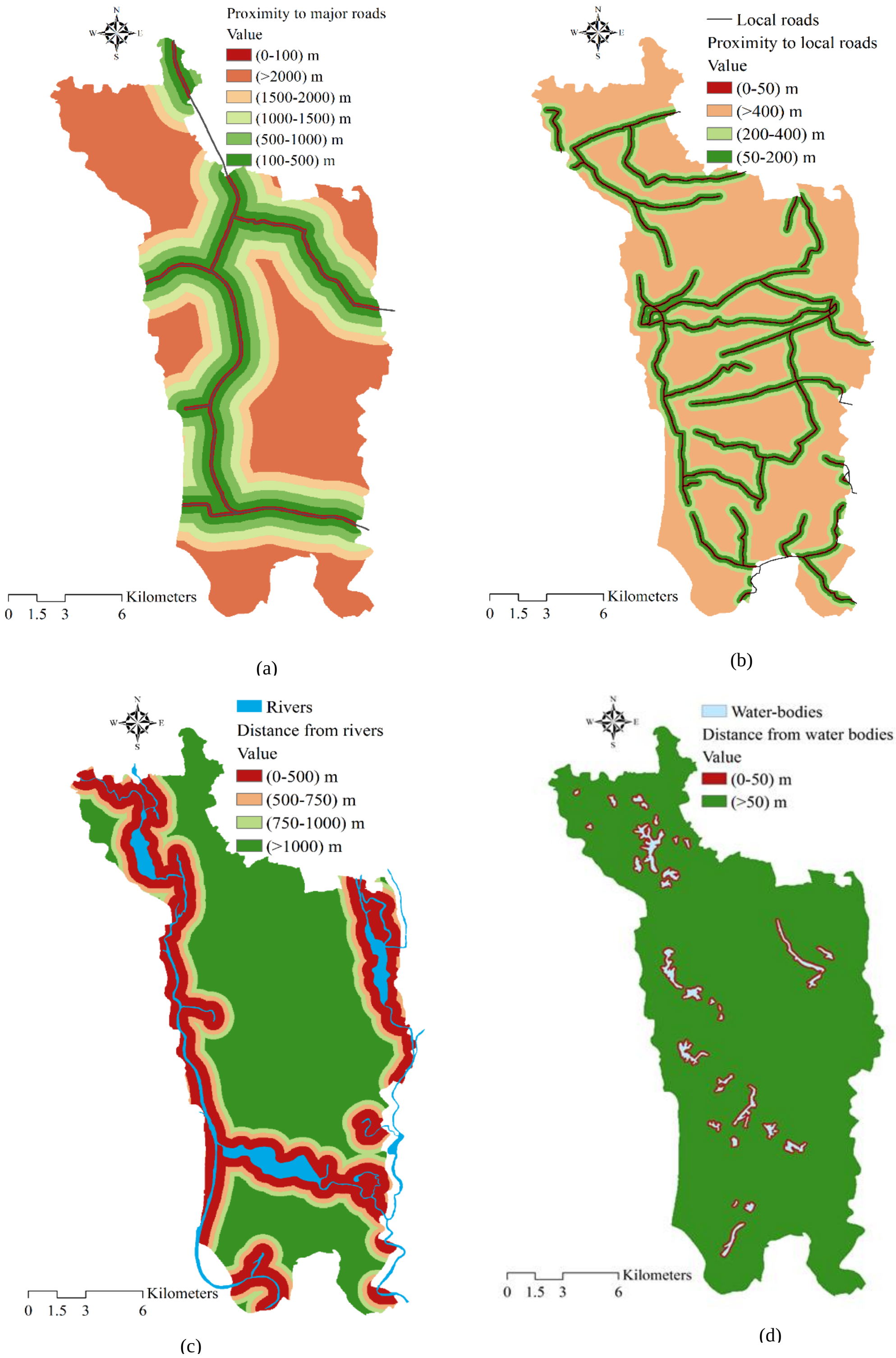


Figure 3.6 Maps resulting from the reclassification of layers using criteria according to the factors and constraints: (a) proximity to major roads; (b) proximity to local roads; (c) distance from rivers; (d) distance from water bodies (Continued)

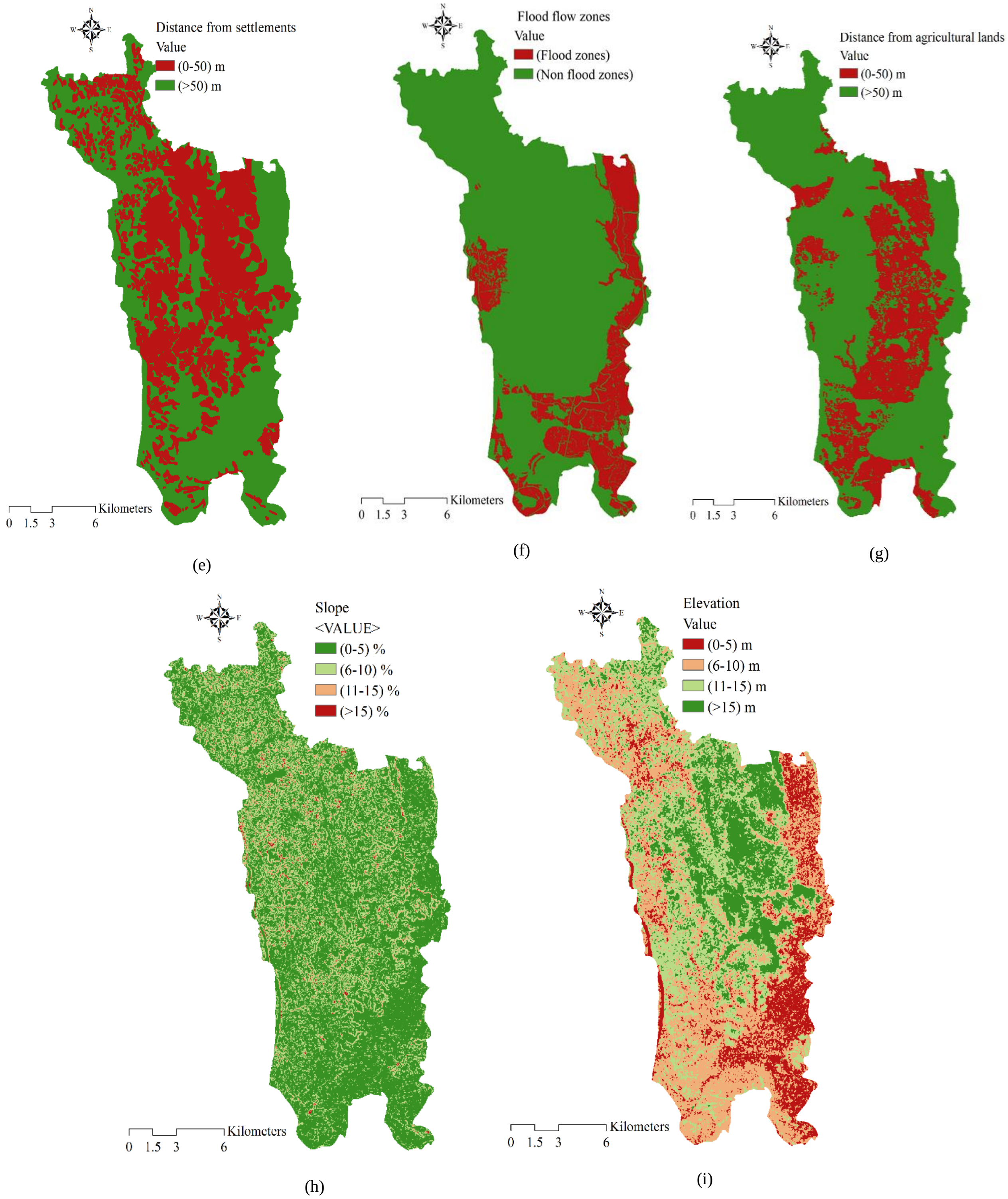


Figure 3.6 (e) Distance from settlements; (f) flood flow zones; (g) distance from agricultural lands; (h) slope; (i) elevation

Table 3.8 Scores and suitability classifications of the factors and constraints.

Name of Criterion	Factor/Constraint	Classification	Suitability	Area (%)
Proximity to major roads	0-100 m	Constraint	Not suitable	4%
	100-500 m	Factor	Most suitable	13%
	500-1000 m	Factor	Moderately suitable	15%
	1000-1500 m	Factor	Less suitable	13%
	1500-2000 m	Factor	Least suitable	12%
	>2000 m	Factor	Suitable but avoided	44%
Proximity to local roads	0-50 m	Constraint	Not suitable	6%
	50-200 m	Factor	Most suitable	15%
	200-400 m	Factor	Less suitable	19%
	>400 m	Factor	Suitable but avoided	60%
Distance from rivers	0-500 m	Constraint	Not suitable	29%
	500-750 m	Factor	Least suitable	9%
	750-1000 m	Factor	Moderately suitable	8%
	>1000 m	Factor	Most suitable	54%
Distance from water bodies	0-100 m	Constraint	Not suitable	5%
	>100	Factor	Most suitable	95%
Distance from settlements	0-50 m	Constraint	Not suitable	46%
	>50 m	Factor	Most suitable	54%
Flood flow zones	Flood Flow Zone	Factor	Suitable but avoided	22%
	Non-Flood Flow Zone	Factor	Most suitable	78%
Distance from agricultural lands	0-50 m	Factor	Suitable but avoided	31%
	>50 m	Factor	Most suitable	69%
Slope	0-5%	Factor	Most suitable	66%
	6-10%	Factor	Moderately suitable	29%
	11-15%	Factor	Less suitable	4%
	>15%	Constraint	Not suitable	1%
Elevation	0-5 m	Constraint	Not suitable	15%
	6-10 m	Factor	Less suitable	36%
	11-15 m	Factor	Moderately suitable	30%
	>15 m	Factor	Most suitable	19%

3.4.4 Industrial Zone Selection

The map resulting from use of the “Weighted Overlay” tool shows the land suitability raster layer. In this map, the cells with different scores were clustered into four groups, “0”, “1-5”, “6-7”, and “8-10”, which correspond to areas that are “not suitable”, “less suitable”, “moderately suitable” and “most suitable” **(Figure 3.7).** Based on the calculated areas of the polygons, 93% of the land in the study area was found to be “not suitable” for industrial sites. On the other hand, only 4% of the land was “most suitable” **(Table 3.9).** The results showed that the spatial analysis worked properly, based on the priority weights of the criteria that were incorporated into GIS using the MCA using AHP. The lands that were classified as “most suitable” for industries were converted from raster layers into vector polygons. According to the measured area for each polygon, only 4 compact zones were found which had areas of at least 10 ha, and these zones are marked in red in **Figure 3.7**.

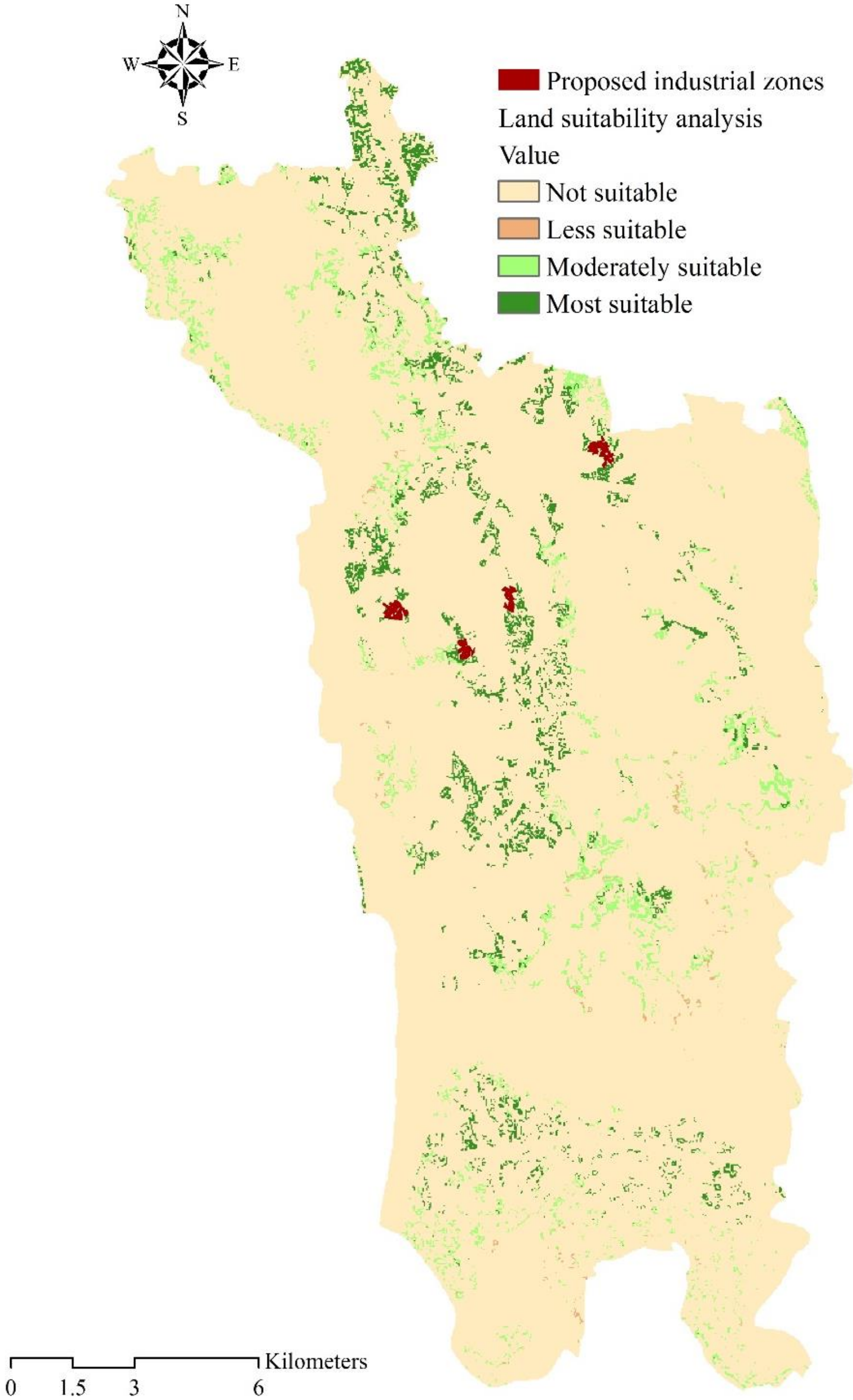


Figure 3.7 Land suitability analysis for industrial sites.

Table 3.9 Area assigned to each group on the land suitability map for industries.

Ranking	Recommendation	Area (ha)	Proportion (%)
0	**Not suitable**	26052.09	**93%**
1-5	Less suitable	0	0%
6-7	Moderately suitable	840.39	3%
8-10	**Most suitable**	1120.52	**4%**

3.4.5 Verification of the LSA

The feature map showing the potential industrial zones within the study area was exported to Google Earth Pro® for verification using the satellite images. The 4 most suitable locations were recommended as potential sites for industrial zones. The individual parcels contained 15.17 ha, 10.28 ha, 10.11 ha and 16.50 ha **(Figure 3.8a, 8b, 8c, 8d).**

(a) 15.17 ha

(c) 10.11

(b) 10.28

(d) 16.50

Figure 3.8 Four most suitable areas: (a) 15.17 ha, (b) 10.28 ha, (c) 10.11 ha and (d) 16.50 ha (Google Earth Pro®, 2016/08/08).

These areas were mostly vacant, located adjacent to major and local roads, and not within flood zones or agricultural lands. However, the images show water bodies and settlements within the most suitable sites, indicating that the results contain some errors. These deviations occur because the vector layers representing the settlements and water bodies were not updated after 2010. The land use within these areas changed subsequently to settlements and water bodies.

3.5 Discussion

The study focused primarily on statistical data covering the agricultural lands within Savar, and these data showed that Savar lost 6% of its agricultural lands over 10 years. However, four of the administrative areas within Savar lost more than 6% of their agricultural lands. The greatest loss was noted for Yearpur, which lost 10% of its agricultural land. On the other hand, the geographical locations of 420 cloth factories which were collected during the field survey showed that the growth of the industries was denser within those four areas. The industries, particularly cloth factories, expanded in Savar over the last three decades. In addition, according to BGMEA data, 77% of the cloth factories were established after 2000. Bangladesh is the 2nd-largest exporter of readymade cloth, and 81% of the export earnings came from this industry in FY2013-14. The economic growth of the nation through expanding manufacturing units influenced the transformation of agricultural lands of suburban areas to industrial zones. Therefore, industrialization has been an important cause of the reduction in agricultural lands in suburban areas. Savar has always been a promising area for the establishment of industries because it is near the capital city of Dhaka and is well connected with the Chittagong port area. In addition, the Dhaka EPZ is also located in Savar.

The novel approach used in this research involved conducting an LSA for industries to determine whether any areas exist that are suitable for the future development of industrial zones. The GIS-based spatial analysis proved to be an efficient tool for identifying suitable lands within large areas with mixed land use distributions while evaluating multiple criteria for the location of new industries. The AHP, a widely used multi-criteria method, enabled ranking and weighting of the criteria used in this part of research. The technique showed that the proximity to major roads had the highest weight (22%) of the nine criteria used, followed by the proximity to local roads (14%) and elevation (14%). The fourth most highly prioritized criterion was distance from agricultural lands (13%). Because Bangladesh is an agricultural country, it is difficult to avoid agricultural lands altogether during the development of new infrastructure. However, the approach used in this study succeeded in protecting the core agricultural lands using spatial datasets in a GIS environment. Considering the agricultural lands as an individual criterion helped to protect the existing agricultural lands.

Finally, combining the factors and constraints using the decision rule in the "Weighted Overlay" tool, the LSA found that only 4% of the study area could be used for industrial expansion in the future. The results certainly showed the most significant aspects of the land use pattern within Savar. Based on the results from the designed LSA, which represents the relevant criteria and factors, the study area is not suitable for further expansion of industries. The area is already occupied with built-up areas and lacks proper land use management. In addition, the study also tried to identify compact zones for industrial development; the use of such zones could be more effective than current practices in promoting sustainable land use. This study found only one potential economic zone that contains 16 ha of land.

However, the outcome of LSA depends mostly on the spatial data set, which must be upgraded with recent changes. In particular, land use maps with settlements are key elements that change frequently. Nevertheless, open-source satellite images have made land use management easier and more relevant for policy makers and researchers. This research approach has the potential to gain credibility in practical implementations in Bangladesh. However, such research needs to include collaborations with government organizations in order to draw the attention of both policy makers and researchers. Furthermore, abandoned property or old industries could be utilized as part of the process of identifying new economic zones to increase the efficiency of land use management. As one example, the Adamjee Jute Mill was established in 1951 in the Narayanganj district of Bangladesh and eventually became the largest jute mill in the world. However, in the 1970s, polypropylene replaced jute, and the mill faced heavy losses beginning in the 1990s. Finally, in 2002, the mill was shut down and handed over to the Bangladesh Export Processing Zones Authority (BEPZA) for conversion into an EPZ. The Adamjee EPZ was opened in 2006. The process of transforming old or abandoned industrial sites into new industrial sites is a long-term planning process, and large investments are needed to remove the disused industrial buildings and reform the operating processes used in these areas. In such cases, economic and environmental assessments are also needed. Thus, the government of Bangladesh encourages the private sector and foreign investors to transform old industries or abandoned and unproductive lands into economic zones. This micro-research approach can be used to consider the different districts surrounding Dhaka, where new and abandoned properties or old EPZs can be included in the analysis as alternative most suitable locations for economic zones.

3.6 Summary

The unplanned growth of industries in the suburban areas of a country drives significant changes in the degree of agricultural land use, and these changes may affect food security in a long run. To address these questions, an LSA model was developed to assess suburban development, particularly industrial growth, and the suitability of further industrial growth, considering environmental restrictions and agricultural land use changes. The model also recommended the further expansion of the most suitable industrial sites and economic zones using GIS and multiple criteria based on environmental factors and the opinions of stakeholders and experts. The GIS-MCA model demonstrated that the transformation of agricultural lands to industrialized areas or urban areas over time reached 11-15% in the suburban areas in the research area. The LSA showed that only 4% of the land within the study area satisfied the basic requirements for industrial expansion. However, locating potential economic zones where industries could be established in compact areas that comply with industrial requirements and environmental ethics was prioritized, and 4 compact zones that could be recommended for industrial expansion were identified. Furthermore, spatial validation analysis and time series data enabled us to observe the land use changes associated with industrial facilities. We found that more than 200 industries were constructed, transforming the agricultural lands, during the last decade. Unlike most developing countries, Bangladesh has a high population density. The lack of land use policies and environmental legislation and the transformation of agricultural lands to industrial areas increases the risk of losing agricultural lands.

The micro-level study showed there is a need for monitoring the land use change in spite of having legal policy planning. Land use monitoring is an inherent part of the land use planning for the policy makers. Besides, researchers and stake holders also seek for a land use/land cover data for decision making. Since the land use monitoring is a retrospective nature study, past data is always needed. On this regard, remote sensing data base has proven a reliable source for monitoring and developing past land use database. Due to open assess of the medium high-resolution satellite data, like Landsat launched in 1972, the land cover mapping has become easier for the researchers. Thus, this research needs to extend further to focus on land cover mapping of past years and to detect the changes on land use. The study also required to upscale from Savar to adjacent sub districts which has the influences on land use and land cover policies of Dhaka and suburban areas.

CHAPTER 4

Land Use Land Cover (LULC) Mapping Using Satellite Remote Sensing

4.1 Background

Land use with respect to urbanization has become a most significant domain of the current era for sustainable development of the global environment. The pressure on the land use is immense due to the growing population of the world. The cities occupying only 2% of the earth land but uses 75% of all resources and generates 75% of the total world waste (UNFPA, 2007). The urban population is now reached to 55% of the world population in 2018. The world urban population percentage will be increased to 68% by 2050 as projected by the UN (UN, 2018). Asia is carrying of 54% of the world's urban population whereas Europe and Africa individually have only 13% of the world's urban population.

The growth of population in the metropolitan areas is the prime driving force to transform the land use of the urban fringe rural areas. The most visible transition is the rural to sub-urban areas, mostly due to the expansion of residential and commercial areas. The transition of the rural land use to sub-urban and urban land use has been considered as one of indicators of the regional economic growth (Rimal, 2011; Hegazy and Kaloop, 2015). However, the advantages of the sub-urban development often compromised with the impacts of ecosystem; environmental hazards, degradation of agricultural lands, vegetation and forests areas. The basic elements of the quality of life of the citizens, such as air and water quality mostly affected by the imbalanced growth of urbanization. In addition, the human behavior with respect to the economic ability of different groups of people causes social disparities, fragmentation (Squires, 2002).

Hence there is a certain need of constantly monitoring the land use changes in the cities and its periphery areas. A sustainable urban development requires sustainable land use planning which in turns replies on land use monitoring and planning. The term "sustainable city" refers that the main cities should be self-supported by using resources produced within or nearby surroundings (Roy, 2009). To produce required resources for a huge population of a city, land use planning holds a major responsibility. However, the major cities are already in a state where it is a most difficult task to rebuilding the land use. Focus now on the urban fringes to re-build, re-think for a sustainable urbanization to meet the need for current population and future generation. It is advised that to incorporate the sustainability for urbanization by stating the required state of an urban area and then identify the approaches and methods to obtain that state (Roy, 2009).

Therefore, the policy makers and stakeholders, researchers always require the up to date geospatial information of the terrain. The emerges of the satellite remote sensing data had triggered the research revolution from the last couple of decades. Globally the satellite remote sensing data has become the most important resources to monitor the land use changes over the time period. In addition, researchers also explore new approaches incorporating multi-disciplinary areas alongside the remote sensing to facilitate the land use and land cover decision making process. Studies of land use and land cover monitoring use remote sensing method across the world in different scenarios. This has already proven that remote sensing potential for regional LULC mapping.

Land use and Land cover (LULC) which significantly affects the regional development and environmental protection. Sustainable use of land is very important for the growing population around the world and meet the Agenda of United Nations. Dhaka city become one of the densely populated regions where LULC analyse is needed for future growth and projection to meet the SDG goals. Rapid change of land uses especially agricultural low lands to settlements by realtor caused drastic decrease of retention areas, which causes inundation during heavy rainfalls in the Dhaka city. LULC change analysis and monitoring is lack off by the government of Bangladesh. There are no strict regulations to follow the land use transformation in Dhaka City. LULC analysis is also required for a periodic interval of time series to understand the change dynamics of land use transformation in a macro-scale using satellite imagery.

4.2 Objectives

The following objectives were considered in this part of research to docus on LULC analysis and land use transformation:

- To perform LULC analysis for monitoring land use planning in a macro scale for the suburban areas of Dhaka city.
- To find out the land use transformation and change dynamics for a periodic interval using time series satellite imagery.

4.3 Materials and Methods

4.3.1 Conceptual Framework

The LULC mapping of two different years were conducted using the Landsat satellite imagery. The satellite data were acquired from the USGS website which has open assesses for the registered users. The images were chosen for the same season, dry season to avoid cloud cover images and to have similar vegetation and agricultural scenarios in spite of having almost a decade interval of two different years. Considering investigated years and Landsat mission timeline of each Landsat sensors, two images were selected from Landsat 5 TM and Landsat 8 OLI **(Section 4.3.3)**. These images were cloud free and the quality of the images were scored 9 (best).

On the other hand, references data **(Section 4.3.4)** were collected from different sources of 2010 to assist during the training sites selection and also for the accuracy assessment. Field survey were conducted to collect ground truth samples for 2017. Since this section has scaled up with all other sib district, a comparatively large area is covered, it would require longer time to visit. The field survey was done to collect 355 points from two sub-districts among the 7 sub districts **(section 4.3.5)**. To validate the accuracy assessment in aggregation with the ground truth data, the study used the most updated geo-database from government source (Survey of Bangladesh, SOB). The geo-database was compiled by the ground verification conducted on 2016. The reference data were further processed in ArcGIS 10.3® for projecting in WGS UTM 1984 Zone 46N. Each layer of interest was processed individually and clip the data to extract the information comprising the study area.

Satellite image pre-processing were done in Erdas® by using layer stacking, mosaic and sub setting for 7 sub-district and the capital city **(Figure 4.1).** The multispectral image was then displayed in false colour composite to identify the objects according to the land cover classes **(section 4.3.8).** Then image enhancement was done using the convolution tool for 3x3 edge enhance. This helped to sharpen the edges of objects of pixels and thus allowed more visibility to separate the individual sub-classes. Though finally seven land cover classes were selected for mapping the LULC, there were sub-classes in individual classes which were easily identified while visual investigation. Thus, spectral signatures were created for individual sub-classes which assist while selecting the training samples. Training samples were taken ranging from 20-40 (pixels 2631-11699) for individual sub-classes. Each training samples were investigated by histogram and the spectral profile evolution. Then the similar training samples were merged for respective sub-classes and the training samples which were not match deleted.

Supervised classification technique, maximum likelihood algorithm was applied for the land cover classification. Based on the field observation, reference data and with the help of the Google Earth Pro® visual investigation was done first to check the credibility of the classification technique. Several misclassification was observed at this stage thus a post classification refinement was needed to minimize the error. Area of interest was selected for visual analysis and the error was corrected by recording the land class within the area of interest to their original class. Finally, the subclasses where merged to their respective classes. A salt and pepper effect were observed to the final map, hence 3x3 majority function tool was applied to eliminate the effect.

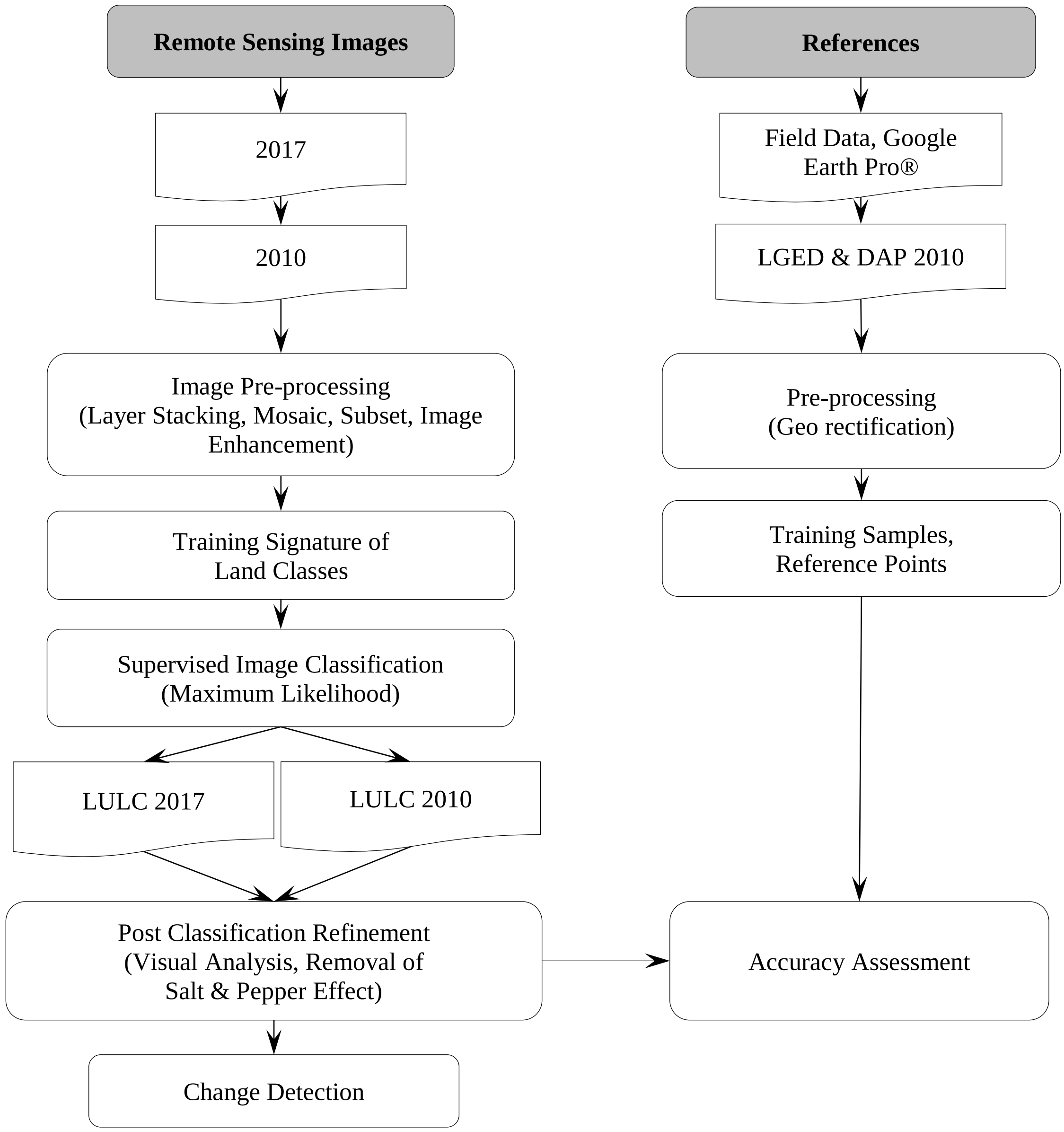
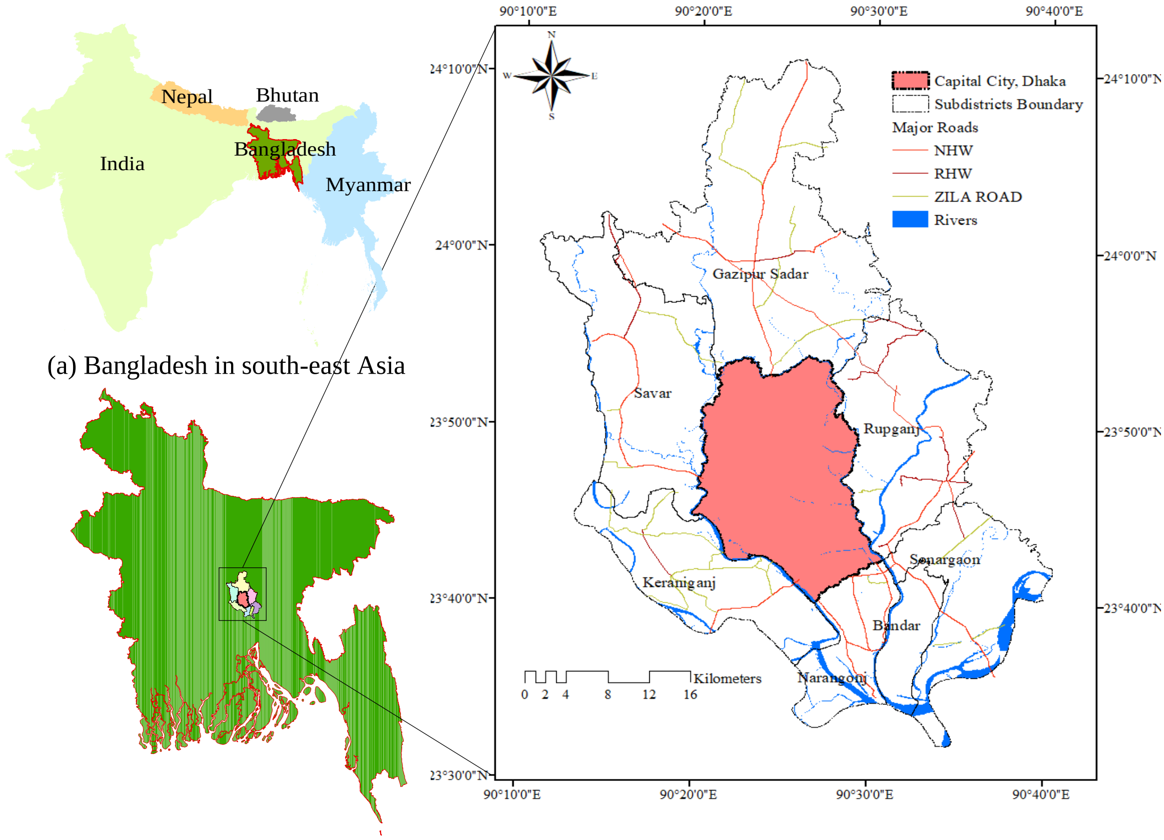


Figure 4.1 LULC change detection analysis flowchart.

4.3.2 Scale up of Study Area

The study area is the capital city of Bangladesh, Dhaka and the surrounding seven sub-districts, named Savar, Keranigonj, Narangonj, Bandar, Sonargoan, Rupgonj and Gazipur Sadar **(Figure 4.2).** The geographic location of the study area situated between the latitudes of 23°44'15.51"N and 23°53'23.94"N and between the longitudes of 90°25'18.06"E and 90°26'20.65"E (degrees-minutes-seconds, WGS84). The elevation is ranging from 1 to 14m and basically a flat plane area of 1714 km^2. The population of this area was 6.5 million in 2011 (BBS, 2011) which was increased by 69% from 2001 (BBS, 2001). The average rainfall of this area is 2000 mm per annum, where more than 80% rainfall occurs during the rainy season from June to September (Dewan and Yamaguchi, 2009a).

The capital city and the surrounding sub-districts are located mainly on the Modhupur terrace (Miah, 1968). The Dhaka capital city bounded by four major rivers Buriganga, Turag, Tongi and the Balu rivers which flows to south, west, north and east respectively. During the monsoon the water level of these rivers always increased and also combined with floodwater overflow from the larger rivers of Ganges, Brahmaputra and Meghna rivers. There are other important rivers such as Dhaleswari river which flows west side Savar to the south and join the Burigonga river, Shitolakkha river flow through Rupganj district.



(b) Bangladesh

(c) Dhaka Capital City and seven adjacent sub-districts

Figure 4.2 Study area location, (a) Bangladesh in south-east Asia, (b) Bangladesh, (c) Dhaka Capital City and seven adjacent sub-districts.

4.3.3 Landsat Data

Landsat data have received tremendous response in the science and applications domain from academic to practitioner's communities since the program had launched. These researches were explored in diverse fields covering land cover change, urban expansion, agricultural production to crop phenology analysis, forestry and biomass, water quality analysis, wetland monitoring, natural disaster risk assessments, archeology and anthropology since 1972 (USGS 2002). Landsat has become a fundamental data source for answering the science questions and also has proven a valuable data source for decision makers. The advent of the Landsat series had started a new era of satellite remote sensing which eventually achieved a global recognition as an asset. Regional to global level, the research institutions, government and non-government agencies, academic institutions utilizing the advantages of this medium spatial resolution satellite data in related fields to compliment decision making process, reporting and to help policy makers (Wulder *et al*., 2012).

The alternation of earth surface is being constantly going on and mostly dominated by the human activity rather than natural process. As land is the primary assets for agricultural production and limited for every country, land use change monitoring has become a core domain for land use planning. Specially, the developing countries where human activities constantly transforming the land use, the policy makers are required to monitor and to detect the change for land use planning.

Although there are numbers of satellite programs operating but few has accessibility for the researchers and practitioners. On this regard, Landsat program is inimitable due to have an archive of series of imagery since the satellite had launched (El-Kawy *et. al*., 2011). The images allow to monitor, map and manage the LULC for a large area and over a long period (Wulder *et al*., 2008). A good number researches has been done in the field of LULC changes, proving the level of accuracy of the LULC analysis using the Landsat imagery.

Thus, this part of the research intended to utilize the Landsat imagery resources for the land cover mapping of two years apart from 15 years. In this research, 2017 and 2010 were considered with focusing on particular season, dry season and cloud free images. Landsat 8 OLI and Landsat 5 TM sensors were found most suitable for the assessment **(Table 4.1).** The data for 2010 was acquired on 30th January of Landsat 5 TM and 17th January for 2017 of Landsat 8 OLI. As the temporal resolution of Landsat is 16 days, it was difficult to find the cloud free images of the same season. January is basically dry season in Bangladesh and thus was accepted that there would not be any runoff water from the larger rivers and the water-bodies would have their original states. According to the Landsat quality rating the images were chosen best as scored “9”.

Table 4.1 Remote sensing datasets.

Satellite Images	Sensors*	Mission Timeline	Path/Row	Acquired Time	Image Quality
Landsat 8	OLI	March 1984- January 2013	137/43 & 44	17th January, 2017	9
Landsat 5	TM	February 2013-Till Date	137/43 & 44	30th January, 2010	9

*Thematic Mapper (TM)
*Operational Land Imager (OLI)

The spatial resolution of the multispectral bands is 30 m whereas the panchromatic of Landsat 8 is 15m. However, the analysis accounted only the multispectral bands: Band 1 to Band 5, Band 7of Landsat 5 TM **(Table 4.2)** and Band 1 to Band 7 of Landsat 8 OLI **(Table 4.3),** excluded the thermal bands.

Table 4.2 Spatial and spectral resolution of Landsat 5.

Bands	Wavelength (micro-meters)	Resolution (meters)
Band 1 - Blue	0.45-0.52	30
Band 2 - Green	0.52-0.60	30
Band 3 - Red	0.63-0.69	30
Band 4 - Near Infrared (NIR)	0.76-0.90	30
Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
Band 6 - Thermal	10.40-12.50	120* (30)
Band 7 - Shortwave Infrared (SWIR) 2	2.08-2.35	30

Table 4.3 Spatial and spectral resolution of Landsat 8.

Bands	Wavelength (micro-meters)	Resolution (meters)
Band 1 - Ultra Blue (coastal/aerosol)	0.435 - 0.451	30
Band 2 - Blue	0.452 - 0.512	30
Band 3 - Green	0.533 - 0.590	30
Band 4 - Red	0.636 - 0.673	30
Band 5 - Near Infrared (NIR)	0.851 - 0.879	30
Band 6 - Shortwave Infrared (SWIR) 1	1.566 - 1.651	30
Band 7 - Shortwave Infrared (SWIR) 2	2.107 - 2.294	30
Band 8 - Panchromatic	0.503 - 0.676	15
Band 9 - Cirrus	1.363 - 1.384	30
Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

4.3.4 Reference Data

Reference data from different government organizations of Bangladesh were used for both visual analysis while selecting training samples and also for accuracy assessment **(Table 4.4).** Since the data were developed by different organizations these were in different projection system. For example, Survey of Bangladesh (SoB) data had the geographical coordination system in WGS 1984 but projected for Bangladesh Universal Transverse Mercator (BUTM) 2010. Thus, these data were re-projected to WGS 1984 UTM 46N to synchronize with Landsat imagery for Bangladesh using ArcGIS® 10.3. The LGED data had the geographical coordination system in WGS 1984. These data were also projected to WGS 1984 UTM 46N. The Digital Elevation Model (DEM) data with spatial resolution 10m was provided by the

Rajdhani Unnayan Kartripakkha (RAJUK). DEM data was also re-projected to WGS 1984 UTM 46N from Bangladesh Transverse Mercator System (BTM), area specific standard UTM projection for Bangladesh.

Table 4.4 Reference dataset from different organizations.

No.	Geo-database	Scale/Resolution	Organization*	Year
1	Administrative boundary	1:25,000	SOB	2016
2	Building and Structures, Facilities	1:25,000	SOB	2016
3	Hydrographic features	1:25,000	SOB	2016
4	Industrial	1:25,000	SOB	2016
5	Transportation	1:25,000	SOB	2016
6	Vegetation	1:25,000	SOB	2016
7	DEM	10m	RAJUK	2010
8	Detail Area Map	1: 50000	RAJUK	2010
9	Administrative boundary	1: 50000	LGED	2013
10	Settlements	1: 50000	LGED	2012
11	Roads & Highways	1: 50000	LGED	2013
12	Rivers	1: 50000	LGED	2012
13	Water-bodies	1: 50000	LGED	2012
14	Forest Area	1: 50000	LGED	2010
15	Google Earth Pro®		January 2017, January 2010	

SOB* Survey of Bangladesh
RAJUK* Rajdhani Unnayan Kartripakkha
LGED* Local Government of Engineering Department

4.3.5 Ground Validation

Field survey was conducted during 2017 and 2018 for the verification of the classified images. The ground information assists to know the actual condition at the study area and help to know the historical information of specific sites. As in this part, 7 sub-districts and capital city was included, the inspection of the ground survey was done on two sub-districts, Gazipur and Rupgonj. The survey attempted to collect geographical information of about 355 points applying random sampling depending on the accessibility in the study area **(Figure 4.3).**

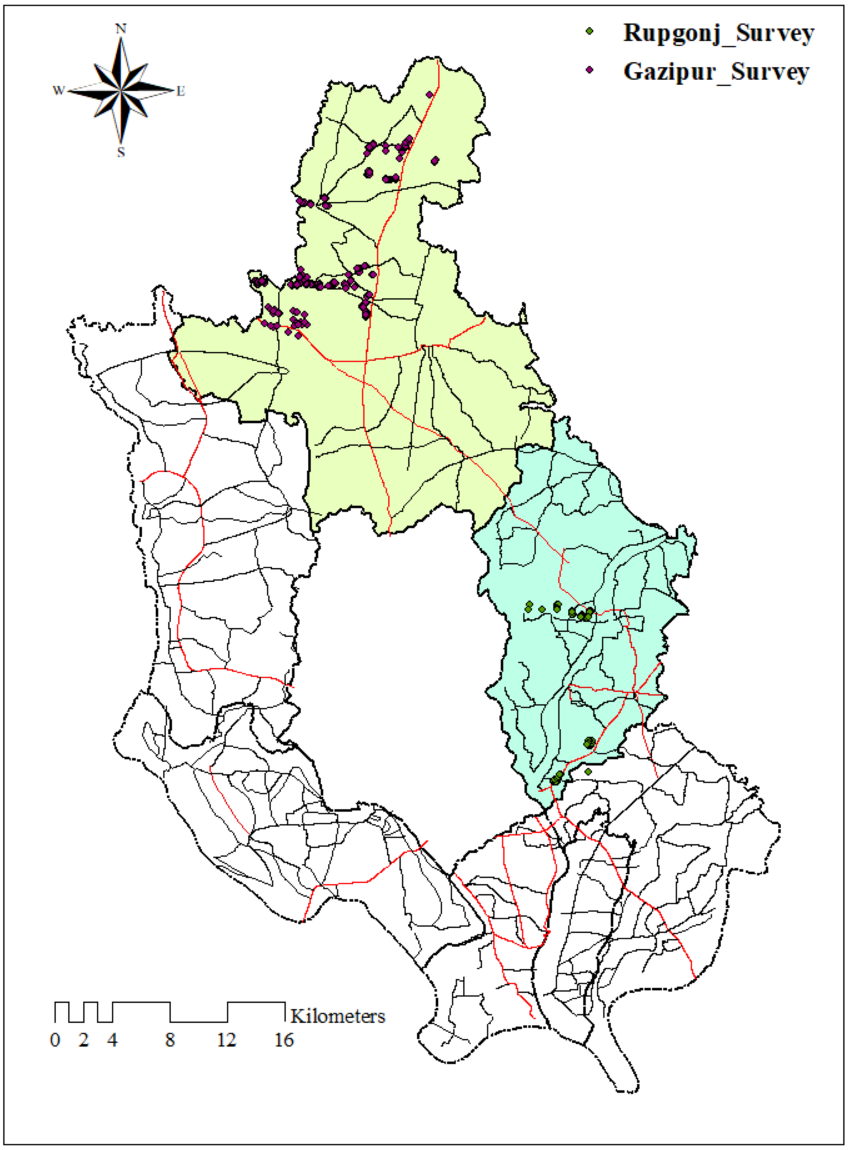


Figure 4.3 Field survey points in Gazipur and Rupgonj.

The 355 points were chosen for 7 land cover types, where agricultural high 68, agricultural low land 32, urban 120, urban transition 20, vegetation 56, forest sal 64 and water-bodies 123 points. The ground truth assists to evaluate the performance of the classification algorithm utilized for the classification system. In addition, the ground truth also determines the connection of the remotely sensed data and the observed elements on the ground (Dewan and Yamaguchi, 2009b). It is advised to do the field survey in the same season or if possible in the same time of data acquisition to avoid the seasonal change in the agriculture and vegetation. Two times field survey was conducted, first 2017 for Gazipur and second 2018 for Rupgong, during March- May. Though the satellite data acquisition time was January however the field survey was done during March-May. This is the transition time from winter to summer, before the monsoon season and also the new season for agricultural production just like in January.

4.3.6 Satellite Image Preprocessing

Satellite image pre-processing is the first step to conduct analysis with the images and is very important due to recognize the relation between the biophysical phenomena and the data stored in the images (Coppin *et al*., 2004). The image pre-processing allows correcting the malfunction of the sensor, the interrupted consequences due to the atmospheric condition and also enhanced the images to improve the quality of the images for visual interpretation. There are number of tools and processes to conduct the pre-processing techniques. The specific tools applied for the pre-processing depends on the objective of the study. The pre-processing is more essential while conducting analysis with multi-date images than to use only a single date. The general steps for image processing are radiometric correction, atmospheric correction, geometric correction, mosaic, extraction of area of interest and some cases masking for unwanted features.

The study considered layers stacking, mosaic, sub-setting and image enhancement as image pre-processing. Landsat data are already geo-referenced in WGS 1984, UTM 46N for Bangladesh. Thus, geo-referencing or geo-rectification was not required. Layer stacking was done with multispectral bands: Band 1 to Band 5 and Band 7 for Landsat 5 TM and Band 1 to Band 7 for Landsat 8 OLI. Since the study area is situated in between two tiles (Path 137, row 43 & 44) mosaic was done after the layer stacking using the ERDAS® followed by sub-setting area using creating an AOI (Area of Interest) from the shape file. The next step was the image enhancement.

Image enhancement could be defined as the alternation of image values to highlight the data in terms of improving the visuality of the image features. The process attempts to improve the ability of balancing human perceptions and computers. In general, the image enhancement is used only for the visual comparison while the automated analysis is done on the original images (Eastman, 2006; Lillesand & Kiefer, 1994). The edge enhancement was performed to highlight the edges of the image by using the convolution tool of 3x3 edge enhancement. In addition, contrast stretching of the two images were performed to visually interpret the land objects in the pixels.

Since seven broad land cover classes were decided for the final land cover mapping, it was necessary to identify the most dominant sub-classes in each category to avoid the spectral confusion in the classes. Thus, the sub-classes and classes were identified by visual interpretation of the satellite imagery. The urban area in the capital city, Dhaka were very prominent as the capital city is already occupied with urbanization. Thus, the samples were chosen with much more pixels than the other land classes. The image was acquired in January, which is a growing season of Boro Paddy. Boro paddy grows in agricultural high land to medium land, these areas were more visible in bright red colour (False composite of NIR-Red-Green). Whereas, due to the aquatic plants on the water-bodies, similar spectral profile was seen as agricultural land. Thus, the agricultural lands of high land were chosen very precisely. In this class, another sub-class where taken as fallow lands, vegetable lands, mixed pixels of cultivated and agricultural crop lands. The inundated agricultural lands which was more visible in the false colour composite (Short NIR-NIR-Red) where chosen as agricultural low lands. These could be regarded as temporary wetlands too as most area of these lands is cultivated once a year. Water-bodies were also very prominent in both the colour composite. The most difficult part was to identify the urban transition class. Firstly, the sub-classes were under the urban transition were finalized. Bare soil, sandy soil was taken under the urban transition. Since the periphery of the capital city, Dhaka is now going in a vast transition where mostly residential areas are dominating followed by industries and commercial places. Some developments were running by the government organizations and rest mostly privately. Thus, huge area spreading over the sub-districted, from small scale to large scale were found as bare soil. The sandy soil had a good number of homogeneous pixels, whereas the bare soils had quite mixed pixels as some fields had grasses.

The enhanced images were used for visual interpretation to identify the LULC classes such as urban, vegetation, agricultural crops, some free water body, bare soil, sandy soil, fallow lands. Due to the mixed land use it was difficult to segregate the land covers elements within this 30m resolution.

4.3.7 Land Cover Classes

The study has adapted the modified Anderson Scheme Level I land cover classification system (Anderson *et al*., 1976). The scheme was originated by the USA to have a uniform classification system throughout the country while using satellite and aircraft remote sensing data. Level I and level II of the scheme are more general whereas level III and Level IV have the flexibility to use as per the feature and requirement, maintaining the basic norms among each level and with the national scheme. The system eventually adopted by the researchers and practitioners around the world. The medium resolution satellite images like Landsat data and air photo in high elevation can extract information for Level I whereas to map for levels II, III and IV comparatively higher resolution and low-elevation air-photo are required.

Although the study attempted to follow the level I, there was a slightly modification to categorize the important features. Thus, this research finally selected 7 main land cover categories, comprising sub-classes in individual category **(Table 4.5).**

Table 4.5 Description of land cover classes.

No.	LULC Types	Descriptions
1	Urban (U)	Residential, commercial area, industries, transportation, mixed urban
2	Agriculture High Land (Agri HL)	Approximately above 10m high
3	Agriculture Low Land (Agri-LL)	Flood plain area, permanent wetlands, seasonal wetlands, low lying areas
4	Vegetation (V)	Trees, homestead forest or trees with settlements
5	Forest Sal (FS)	National forest zone of special tree called Sal
6	Water-bodies (WB)	Rivers, ponds, lakes, water cannels
7	Urban Transition (UT)	Sand, exposed soil, under development of urban land use, brick fields

4.3.8 False Colour Composite

Each spectral band represents a grey-scale image. Three of these bands can be assigned to the display colours red (R), green (G) and blue (B) to obtain a full-colour image. The visual color of individual bands of a multispectral image in computer would appear in a random manner. Thus, each element of the image does not display in its original color. This phenomenon is called false color composite image. There are many combinations of bands for displaying false color composite. Depending on the targeted object to be identified, some combinations are very useful and commonly used for LULC analysis (Ashraf *et. al.,* 2011; Manugula & Veeranna, 2018)

Two false colour composite schemes were considered to identify the land cover objects. Since the band numbers are different for Landsat 5 TM and Landsat 8 OLI for individual range of spectral resolution, the band combination for false colour composite to display the colours for the red (R), green (G) and blue (B) were different. The first false colour composite which had used for Landsat 5 TM and Landsat 8 OLT has shown in **Table 4.6.**

Table 4.6 False Colour Composite (NIR-RED-GREEN).

Display Colour			False Colour	Spectral Resolution	Landsat 5 TM Bands	Landsat 8 OLI Bands
R	Red		NIR	0.76-0.90	4	5
G	Green		RED	0.63-0.69	3	4
B	Blue		GREEN	0.52-0.60	2	3

The display image was helped to identify the vegetation in the image, showed in different shades of red colour varying on the vegetation types and stages. Depending on the photosynthesis process of the leaves and canopies of different vegetations have different reflectance value in NIR band. The urban area, bare soil or the area under transition to urban were appeared in a shade of blue colour depending on the composite and water in showed nearly in black colour **(Figure 4.4).** However, the display colour was not much appealing to identify the different stages of agricultural lands such as low land agriculture, cultivated lands or mixed agricultural lands.

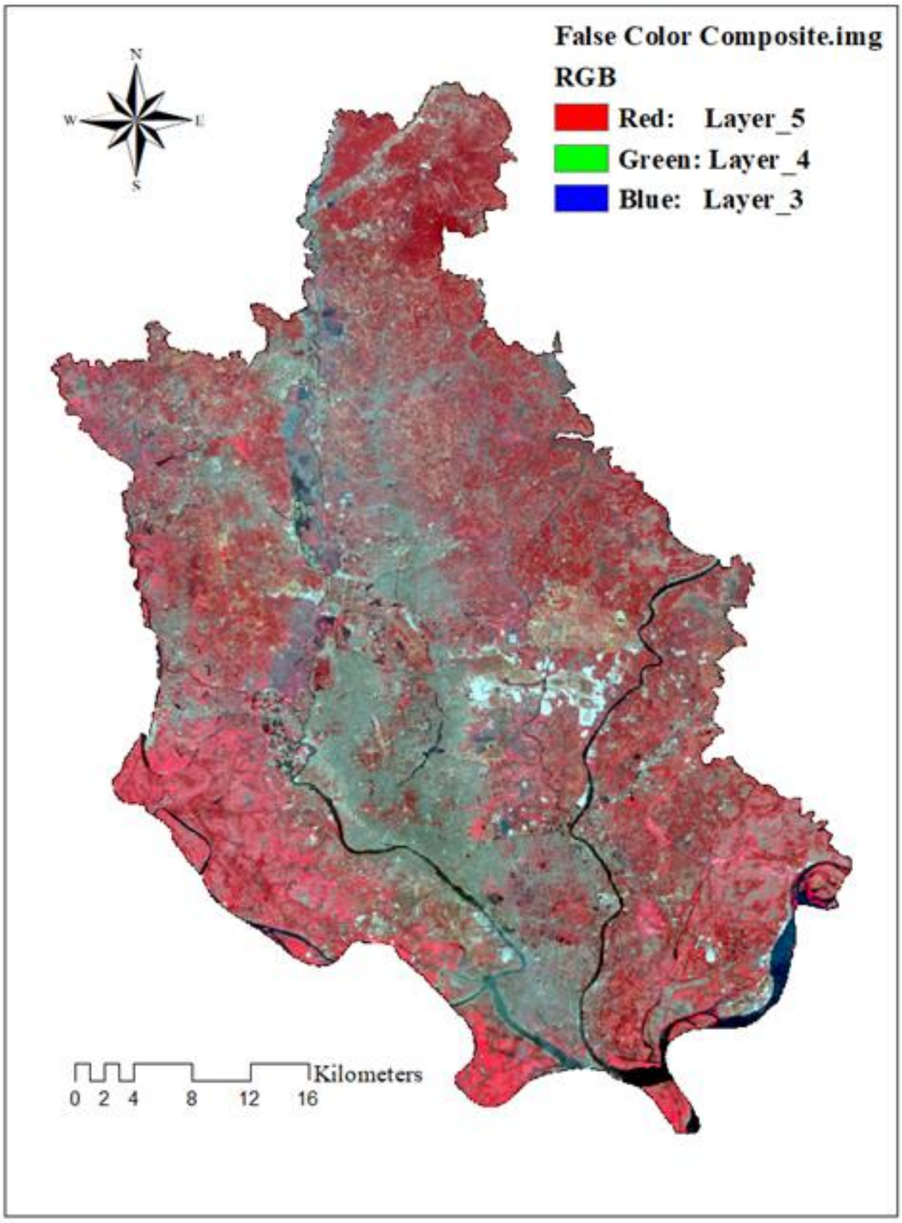


Figure 4.4 Display colour for the false colour composite of Landsat 8 (NIR-RED-Green (5-4-3)).

The second colour scheme was (NIR, Short-wave NIR and Red) **Table 4.7**. The colour scheme was much more appealing to identify the different types of agricultural lands like low land agriculture, high land agriculture, mixed agriculture. The display colour allowed to differentiate the natural forest and other normal vegetation with trees, homestead trees **(Figure 4.5).** However, there were not much different in display colours for bare soil or urban transition area and cultivated lands in both colour schemes.

Table 4.7 False Colour Composite (Shortwave IR-NIR-GREEN).

Display Colour			False Colour	Spectral Resolution	Landsat 5 TM Band	Landsat 8 OLI Band
R	Red		SWIR	1.55-1.75	5	6
G	Green		NIR	0.76-0.90	4	5
B	Blue		RED	0.63-0.69	3	4

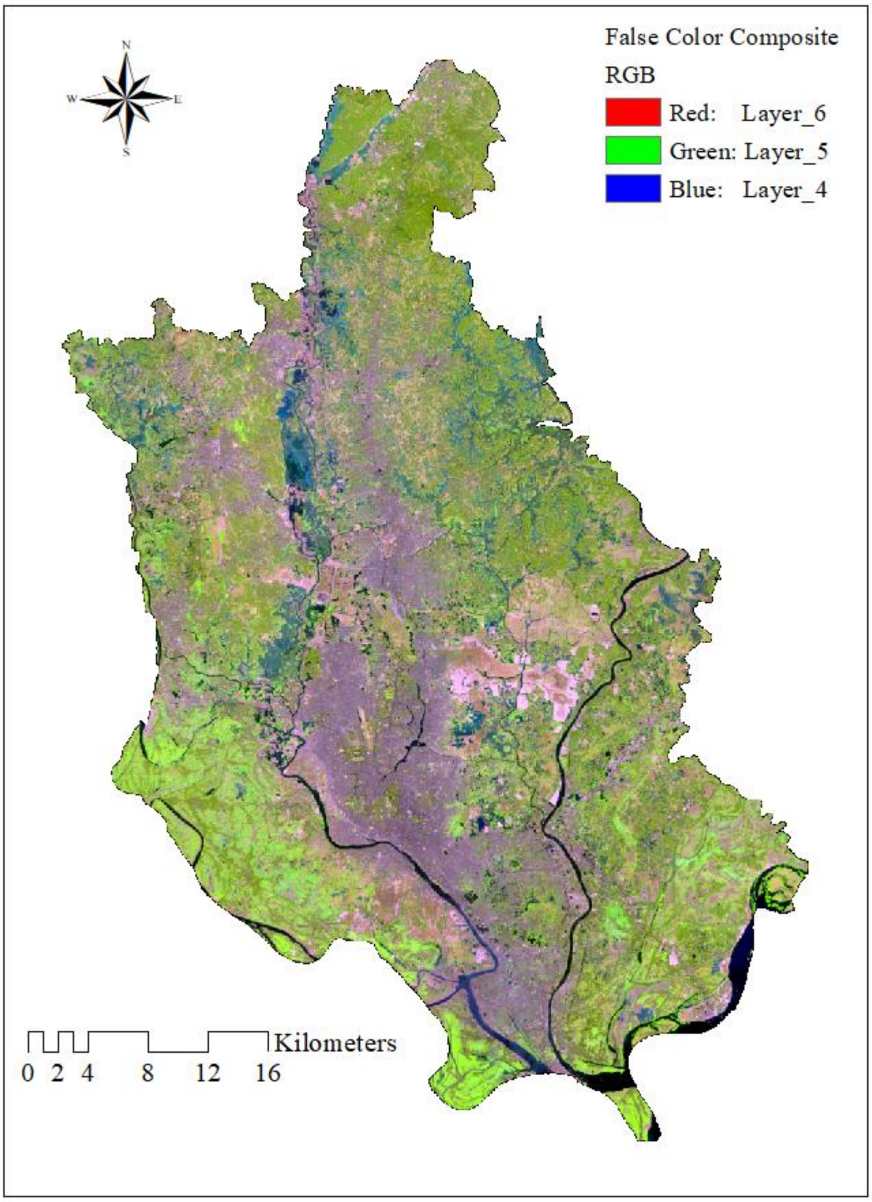


Figure 4.5 Display colour for the false colour composite of Landsat 8 (Shortwave IR- NIR-RED (6-5-4)).

4.3.9 Land Use/ Land Cover Classification

The Land Use/Land Cover classification is the procedure to classify each of the land cover of a particular area of a specific time period. Satellite image is one of the major resources to execute the land classification process of desire time. Multispectral data are widely used to execute the land classification where each pixels of the digital image is categorized into specific land cover class according to the spectral reflectance of behavior each class. The process follows specific decision rule based on the chosen classification technique. The resultant image is then used to present the thematic maps. The purpose of image classification is to display and classify the objects of the terrain appearing in an image presenting the original land cover features on the ground (Lillesand and Kiefer, 1994).

There are two main classification techniques, (1) Supervised and (2) Unsupervised. Since the study has chosen medium spatial resolution satellite image from Landsat, pixel based supervised classification technique is the most appropriate technique.

4.3.9.1 Supervised Classification

In the supervised classification technique first pixels are identified of same land cover which is called “training sites”. The training sites helps to evaluate and to define a statistical phenomenon of the reflectance of each land cover. The process is referred as “signature analysis” and could develop the characterization of the reflectance values by determining the mean value only or characteristics of individual bands for specific land cover or could provide the elaborate analysis of mean, variances and covariances of all bands. It is important to make the signatures to cover maximum features presenting on the ground and to take the sites from a homogenous area of pixels of individual features. Once the signatures are defined with the statistical characterization, the classification of the targeted image is done by evaluating the reflectance value of each pixel with signatures. Finally, the software makes the decision about which pixel would have most similar statistical patterns as the signature (Eastman, 1995).

4.3.9.1.1 Maximum likelihood Classification

The maximum likelihood classification could be defined as a statistical decision criterion which guides during the classification process to allocate a pixel with the highest probability when the signatures are overlying. This classification process came from Bayes theorem which states that a posteriori distribution $P(i|\omega)$, i.e. the probability that a pixel with feature vector ω belongs to class i, which is given by:

$$P(i|\omega) = \frac{P(\omega|i)P(i)}{P(\omega)} \tag{4.1}$$

Here, $P(\omega|i)$ is the likelihood function, $P(i)$ is the priori information, i.e., the probability that class i occurs in the study area and $P(\omega)$ is the probability that ω is observed, which can be written as:

$$P(\omega) = \sum_{i=1}^{M} P(\omega|i)P(i) \tag{4.2}$$

Where M is the number of classes, $P(\omega)$ is often treated as a normalisation constant to ensure $\sum_{i=1}^{M} P(i|\omega)$ sums to one. Pixel *x* is allocated to class *i* by the rule

$$x \in i \ if \ P(i|\omega) > P(j|\omega) \text{ for all } j \neq i \tag{4.3}$$

It is assumed that the data of a given class i follows a multivariate Gaussian distribution in Maximum Likelihood process. Due to the bell-shaped density curve the Gaussian distribution also called as a normal distribution or bell curve distribution. Gaussian is considered as one of the important statistical behaviour phenomenon which can be implemented to ask any questions in the area of image processing and computer vision. Furthermore, pattern recognition field also used Gaussian distribution very often.

It is now easy to express the log likelihood (or discriminant function) as maximum likelihood procedure follows a multivariate Gaussian distribution. So, it could be written as:

$$g_i(\omega) = \ln P(\omega|i) = -\frac{1}{2}(\omega - \mu_i)^t C_i^{-1}(\omega - \mu_i) - \frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln(|C_i|) \tag{4.4}$$

As log is a monotonic function, Equation (4.3) is equivalent to:

$$x \in i \ if \ g_i(\omega) > g_j(\omega) \ for \ all \ j \neq i \tag{4.5}$$

Now each pixel is allocated to the class which has the highest probability or likelihood of that class with the signatures and if the values of the probability are less than a defined value then the pixel will be unclassified. The maximum likelihood classification method is presuming to deliver more reliable result assuming that each pixel follows a **Gaussian distribution** and the signatures were selected accurately (Bolstad and Lillesand, 1991).

The process which was followed for the maximum likelihood is given below:

1. First the number of the land cover types of the study area was determined.
2. The training pixels of individual classes and sub classes were chosen according to the study area observation, reference data sources and checked with Google Earth Pro®.
3. Spectral profile, histogram of each training signature of individual classes were checked.
4. The training signatures which were matched by evaluating the spectral profiles, were merged to the respective classes and those which had difference or confusion to have similar spectral profile were deleted.
5. Then the next step was to derive the mean vector and covariance matrix of the training pixels of individual classes.
6. Lastly, each pixel in the image is now assigned to one of the land cover type or categorized as unknown if the pixel does not meet the threshold value of the probability.

Further, individual class is bounded in an area in multispectral space in maximum likelihood classification where the discriminant function is higher than all other classes. However, decision boundaries are applied to separate the class areas. It could be written as the decision boundary applies between class *i* and *j* when:

$$g_i(\omega) = g_j(\omega) \tag{4.6}$$

For multivariate normal distributions, this becomes:

$$-\frac{1}{2}\,(\omega-\mu_i)^t C_i^{-1}(\omega-\mu_i) - \frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln(|C_i|) - (-\frac{1}{2}\,\left(\omega-\mu_j\right)^t C_j^{-1}\left(\omega-\mu_j\right) - \frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln\left(\left|C_j\right|\right) = 0 \tag{4.7}$$

which can be written as:

$$-(\omega-\mu_i)^t C_1^{-1}(\omega-\mu_i) - \ln(|C_i|) + \left(\omega-\mu_j\right)^t C_j^{-1}\left(\omega-\mu_j\right) + \ln\left(\left|C_j\right|\right) = 0 \tag{4.8}$$

The function is called quadratic function in N dimensions. Thus, only two classes are considered where the decision boundaries are conic sections (Ahmad and Quegan, 2012).

4.3.10 Post Classification Refinements

4.3.10.1 Misclassification Correction

The visual inspection based on the observatory knowledge, field survey and ancillary data were a proved a reliable supportive data source to inspect the resultant map of the supervised classification maps. Due to spectral confusion there could be misclassification among the classes and sub-classes. Thus, prior to proceed for accuracy assessment some corrections by visual inspection were recommended (El-Kawy *et. al*., 2011). Since the study area is very heterogeneous for every land classes within small area, there could be possible to have misclassification since the spatial resolution of landsat is 30 m.

While inspecting most misclassification was found in the urban land and bare soil, the urban areas which had bare soils in the surrounding places appeared as bare soil. In addition, the roofs of the urban structures were also very confusing due to different composite. These also caused to have similar spectral profile of bare soil. Another misclassification was occurred between bare soil (sub-classification of urban transition classification) and fallow lands. Since the acquisition time was in January, many fields were seen as fallow lands or early stage of cultivation. These misclassifications were corrected by drawing for the area of interest (AOI) and then the class was recoded to its original class.

Misclassification also happened between natural forest (Forest sal) and vegetation. This natural mainly named after the most dominated plant species which is called sal tree, the scientific name is (Shorea robusta). The forest could be categorized as "'Tropical Moist Deciduous Forest'. The bio-physical properties like topography and soil quality as well as weather condition are the main elements to control the distribution of sal forest. The forest is consisted over an area of 121,000 ha, containing about 32% of the total forest area (BFD, 2014). The forest is widely spread but having an interrupt distribution in the central and northern part of the country which is quite drier part of the mainland. Thus, a portion of the sal forest is reported in the, Gazipur, sub-district areas. In the satellite image the sal forest appeared in dense dark red in the (NIR-RED-GREEN) colour composite compare to the other vegetation. However, some pixels of the vegetation were found misclassified by the forest Sal.

4.3.10.2 Salt-and-Pepper Appearance

The classified image often appears with a salt and pepper like features resulted from the spectral characteristics variability which encountered during the classification process on each pixel (Lillesand and Kiefer, 1994). A "smooth" classified image is always desirable to visualize the dominant land covers which is expected to give correct image despite of removing the salt and pepper effect.

Majority filter is one of the application which is often used for smoothing the classification. The application uses a 3x3 or 5x5 or 7x7 moving window of pixel and passes over the classified image. The rules for these windows are, if the center pixel of the defined window is not in the majority class then the pixel land class is transformed to the majority class. On the other hand, if the majority class is absent in the defined window, the class of the land cover does not change. While the selected window progresses over the image data, the tool only used the original class reference not the derived class from the earlier window location (Eastman, 1995). Decision rule could be implemented to preserve certain boundaries between land cover areas of interest and also adjust the filter to apply only for a defined area for any specific land cover type (Lillesand and Kiefer, 1994). The majority filter function could be applied more than once to smooth the data. However, care must be given to preserve valuable data, as it may alter the actual amount of each land cover. Especially, it is very important when dealing with mix land use area.

4.4 Results and Discussion

4.4.1 Thematic LULC of 2010 and 2017

The classified land covers of 2010 and 2017 are shown in **Figure 4.7** and **Figure 4.8** respectively. The spatial pattern of the 2010 showing that urban areas, agricultural lands both high land low lands are dominating. The urbanization of the Dhaka capital city has spreaded outskirts to the north in Gazipur sub-districts, mainly towards the National High Way from Dhaka towards Gazipur. The urbanization further moved to south to the Keranigonj sub-districts mainly in the Buriganga river banks located between the periphery of Dhaka and Keranigonj. The low agricultural land was observed between the periphery of Dhaka and Savar sub-districts, mainly the river banks of Turag. In addition, a large area of the east part of Dhaka and Rupgonj sub-district have low land agriculture. Another, important feature was urban transition which was clustered from bare soil and sandy soil observed in the Rupgonj.

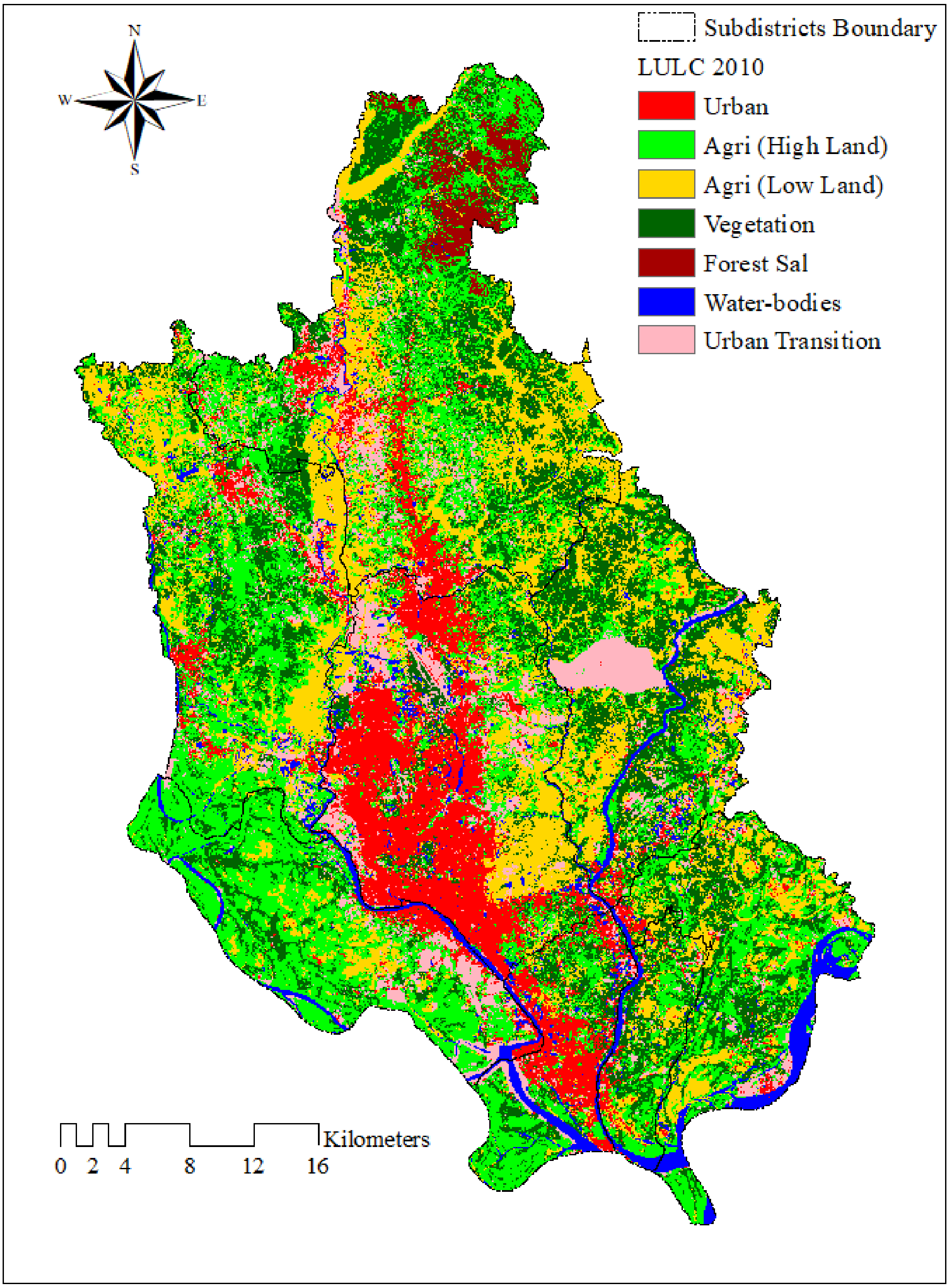


Figure 4.6 Thematic map of land use and land Cover (LULC) of 2010.

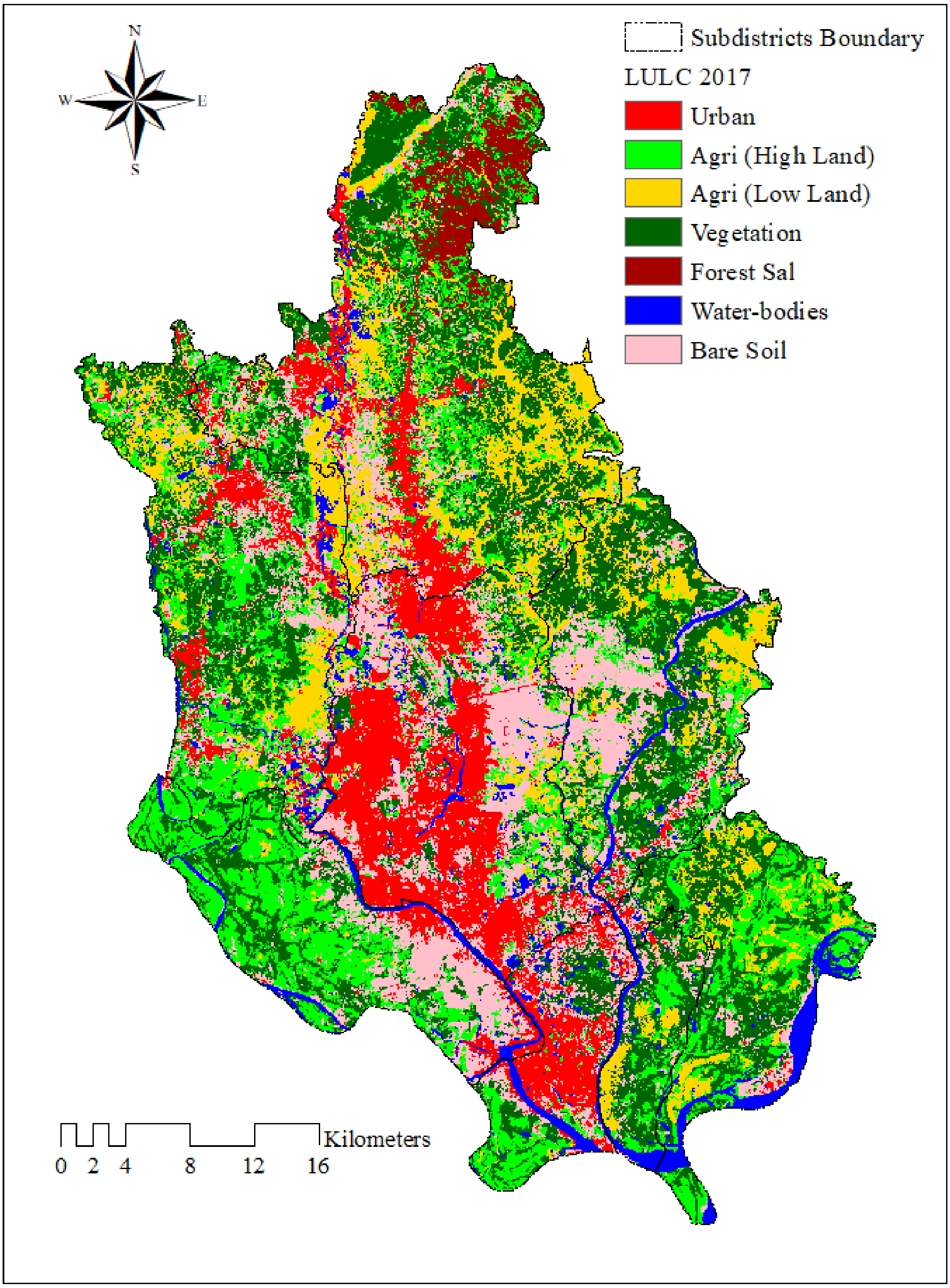


Figure 4.8 Thematic map of land use and land Cover (LULC) of 2017.

The most visible site of the urban transition in Rupgonj is the Purbachol project of the Government organization, a project for a future modern city, which is still under development. Apart from the urbanization, the forest Sal is also visible in the north part of the Gazipur Sadar sub-district. This also proved that the remote sensing data is able to identify the deciduous forest easily. The vegetation showing in the sub-districts mostly bounding rural settlements. The rural settlements spread mostly around the agricultural lands and bounded by the home garden, trees and were very small compare to the 30 m resolution of the Landsat data. Thus, these settlements were not detected as a separate land cover, instead these were incorporated in the vegetation land cover class.

The LULC 2017 shows the urbanization had increased compare to the 2010, moving in the same directions (Figure 4.8). On the visual analysis of LULC 2017 map, the agricultural high and agricultural low, forest Sal did not have much difference from LULC 2010 map, but vegetation had increased from 2010.

The most dominating class was reported for urban transition. The urban transition area was increased rapidly. The government projects Purbachal has expanded more on the Rupgonj sub-district. In addition, the keranigonj sub-districts mostly covered by the urban transition. These areas are now developing by both private and government organizations. To improve the communication between the capital city and other divisions of the country, the government has taken a number of initiatives on road networking. In 2017, the eight lane high way roads which connected the second largest city and port hub, Chittagong, was inaugurated. Starting from the construction of this road, the urban transition on the southeast area has increased with a hike in the land price. Another, eight lane high way is under construction, which will connect the southwest area of the country to Dhaka capital. This construction is going on the from the Jatrabari side of Dhaka through Keranigonj sub-districts. During the field visit in 2018 in Keranigonj a massive urban transition was observed in this area, dominating by the real estate business and privately owners.

4.4.2 LULC Statistics for 2010 and 2017

The resultant thematic classified maps of LULC 2010 and 2017 derived from the supervised classification were used to calculate the area coverage under each category of land cover. In

2010, agricultural high land, low land and vegetation were mostly dominating covering 28.27 %, 20.97 % and 22.75% respectively, whereas Urban had 12. 39% and urban transition had 9.19% **(Table 4.8).**

In 2017, major changes were observed in the urban transition, dominating other land covers along with the vegetation with 18.90 % and 27.38 % land area respectively. The urban area and agricultural low land had almost same area 14.13% and 13.24 % respectively whereas agricultural high land had slightly more than the agricultural low land, 19.01 % **(Table 4.8).**

Table 4.8 Results of the LULC classification of 2010 and 2017.

LULC	2010			2017		
	Area (km^2)	Area (ha)	Percentage (%)	Area (km^2)	Area (ha)	Percentage (%)
Urban	225.58	22557.78	12.39	257.46	25745.58	14.13
Agriculture (High Land)	514.55	51454.53	28.27	346.25	34625.43	19.01
Agriculture (Low Land)	381.62	38162.34	20.97	241.14	24113.70	13.24
Vegetation	414.03	41402.97	22.75	498.85	49885.20	27.38
Forest Sal	29.69	2969.19	1.63	39.00	3899.61	2.14
Water-bodies	87.42	8742.42	4.80	94.73	9473.22	5.20
Urban Transition	167.23	16722.54	9.19	344.35	34434.54	18.90

The graphical representation shows that the urban transition has increased in 2017 than 2010 **(Figure 4.8).** Agricultural high land and low land both have decreased in 2017 compared to 2010. Forest Sal and water-bodies have slightly increased in 2017.

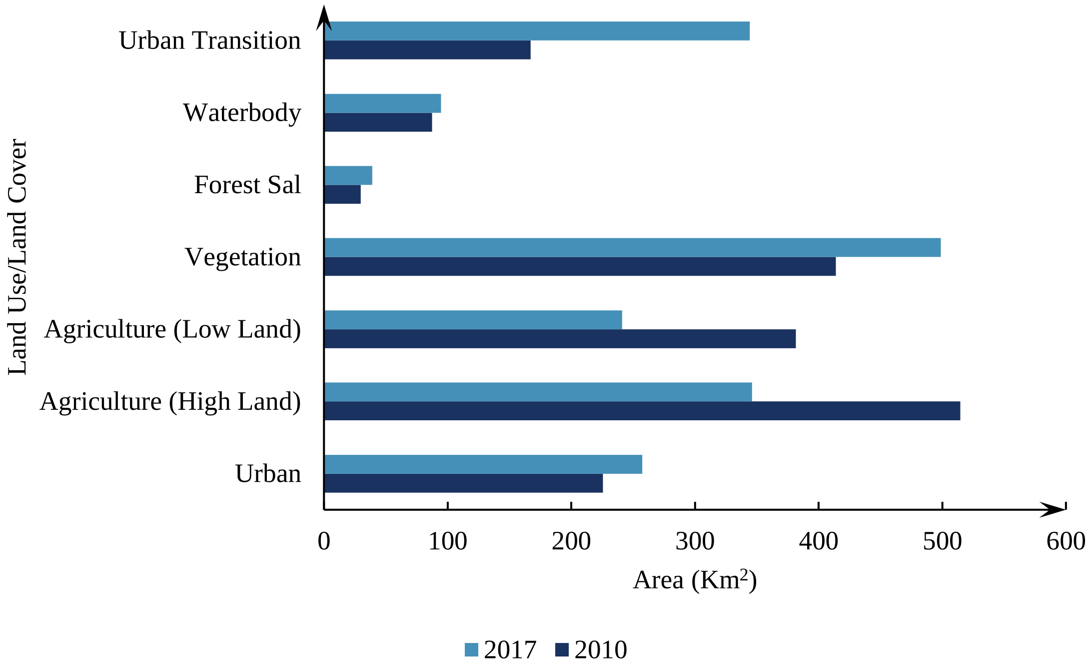


Figure 4.8 Land use coverage area in 2010 and 2017.

The LULC had a dynamic change from 2010 to 2017 **(Table 4.9).** The most significant change occurred in urban transition in 2017, increased by more than 100% from 2010 which certainly reflects that a massive urban development now taking place. The second highest increased was reported for Forest Sal and vegetation, increased by 31.34 % and 20.49 % from 2010. The urban area has increased 14.13% in 2017 from 2010. However, another major changed occurred in agricultural lands both high land and low land, which decreased by 32.71 % and 36.81 % respectively **(Figure 4.9).**

The annual growth rate was 15.13% for urban transition, which was reported as very high **(Table 4.9).** The agricultural high land and low land both were decreased by 4.67% and 5.26% every year, which is very much concerning for agricultural sector. On the other hand, urban expansion was increased by 2.02 % annually.

Table 4.9 Dynamics of the LULC from 2010 to 2017.

LULC	**Percentage Increase/ decrease (+/-)**	**Yearly Increase/ decrease rate (+/-) (%)**
Urban	14.13	2.02
Agriculture (High Land)	-32.71	-4.67
Agriculture (Low Land)	-36.81	-5.26
Vegetation	20.49	2.93
Forest Sal	31.34	4.48
Water-bodies	8.36	1.19
Urban Transition	105.92	15.13

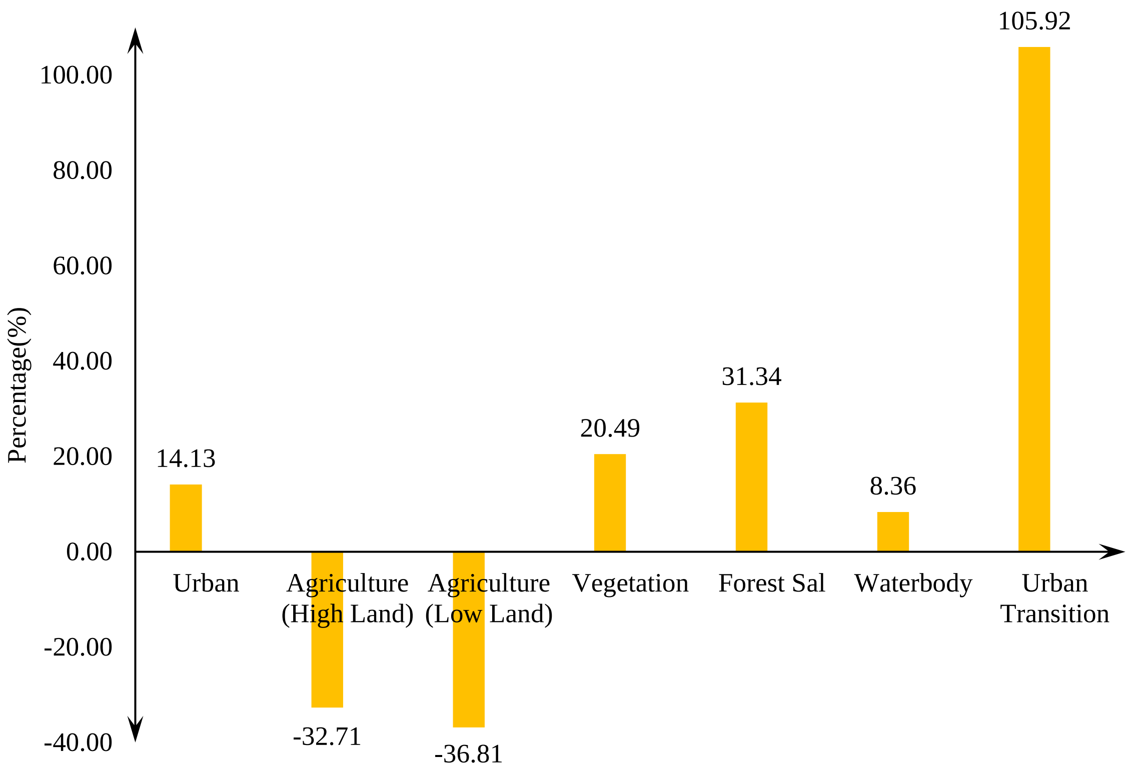


Figure 4.9 Dynamics of LULC change during 2017 to 2010.

4.5 Summary

The LULC analysis for mapping the land cover of 2010 and 2017 has enabled to know land coverage of individual land classes. The recent land cover maps, a parted almost a decade has significant changes in urban transition and agricultural lands. The urban transition has increased at a rapid pace probably much more than any previous decade. The hike in the urban transition is a reflection of the urban developments, which takes place in the adjacent sub-districts around the capital city Dhaka. In 2010, agricultural high land, low land and vegetation were mostly dominating covering 28.27 %, 20.97 % and 22.75% respectively. Again in 2017, vegetation, agricultural high land and urban transition were mostly dominating covering 27.38%, 19.01% and 18.90% respectively. The LULC analysis also reported that there is a declined in agricultural lands both high and low lands at a rate of more than 4%. On the other hand, the urban area has increased 14 % in 2017 than in 2010. However, the urban transition state could be turnout a massive increase in urbanization in coming decades. The declined in agricultural land is a threat for the food security and environmental protections. The satellite remote sensing applications of Landsat data in the field of land use monitoring has brought an evolution in land use planning and monitoring. The open source satellite images had enable the researchers to execute the scientific analysis and incorporate the result in real world. Although the visual analysis of the LULC maps were seem deem acceptable for further analysis, however the thematic maps required assessing for accuracy.

Furthermore, to accept the results from LULC analysis, validation of classification is required with reference to ground truth data and understand change detection. The accuracy assessment is needed on both the images to evaluate the performance of the land classification A sample size of 280 points using stratified random sampling method can be considered for classification for 2017 and 2019 image datasets. In the following chapter, the accuracy assessment and change detection has been discussed in more details.

CHAPTER 5

Accuracy Assessment of Land Use Classification and Change Detection of Land Use Transformation

5.1 Accuracy Assessments

Accuracy assessment is a widely used term to differentiate the classified image with the geographical data that are considered to be accurate to judge the accuracy of the classification procedure. Accuracy assessment is also referred to as validation of the classified image. Generally, it is expected that the accurate data are collected from the field survey. However, practically it is always not possible to take the ground truth data or verify every pixel of a classified image, especially when the test site is large. High-resolution imagery, aerial photos, available data classified maps could be used to derive the ground truth data. Thus, a considerable set of reference pixels is preferred to use for the accuracy assessment. These reference pixels are taken from the classified data of which the ground truth or accurate data are known. The reference pixel usually selected randomly (Congalton, 1991).

Campbell (2007), defined accuracy assessment as it measures the agreement between a standard assumed to be correct and a classified image of unknown quality. USGS (1990) defined, “the closeness of results of observations, computations, or estimates to the true values or the values accepted as being true”. Users perspective it terms of their specific objective has to considered. Thus, it is recommended that users should be able to determine whether the degree of the accuracy of the classified map is suitable to meet their objectives or not (Aronoff, 1982).

The precision of the classification is depending on the level of detail would found in the classified image. The accuracy level could be increased by limiting the amount of detail or by simplifying to comprehensive classes rather than very precise class. The errors of the remote sensing thematic maps could be occurred for various reason such as for geometric error, inappropriate or uncomplete atmospheric correction, incompatible sensor selection for the specific objectives, and unidentified pixels. Thus, it is necessary to identify the source of errors and try to eliminate as much as possible before doing the accuracy assessment. Once the level of uncertainty decreases, the level of accuracy increases; then the classified map can be used for further analysis of scientific research and could be a tool for policy making.

5.2 Change Detection

Change detection is a procedure to observe and to find out the changes of the condition of an object or phenomenon at different times (Singh, 1989). Change detection in the field of remote sensing is widely used in application of land use and land cover (LULC) changes. The most useful application areas are to detect the changes in urban sprawl, coastal area changes, agricultural land use pattern changes, deforestation detection, mining activities observation and landscape changes. Land use is a part and parcel of sustainable development, that's why it is very important to have very authentic, precise and continuous data of LULC changes from local to global levels. The data serves as a supporting tool for any decision-making process regarding land use and could provide solutions for environmental hazards, socio-economic problems (El-Kawy *et. al*., 2011).

5.2 Objectives

LULC-classification accuracy assessment is very important to validate the legislation procedure and confidence in land use change monitoring system for the suburban areas including Dhaka City. The change detection is also required to understand land transformation over a time period in the suburban areas including Dhaka City. In this regard, Landsat 8 OLI datasets need to define with higher classification accuracy for post classification comparison. Post classification change detection has the potential to provide the size, distribution of change areas (either negative or positive) for a period time in the suburban areas including Dhaka City. Therefore, the following objectives were considered in this part of the research.

- ❑ To perform accuracy assessment of developed LULC 2010 by local government authorized reference data for suburban areas in Dhaka city.
- ❑ To perform accuracy assessment of developed LULC 2017 by government most authorized updated reference and ground truth validation in suburban areas in Dhaka City.
- ❑ To perform post classification change detection (pixel by pixel) analysis from LULC 2010 to LULC 2017.

5.3 Methodology

5.3.1 Accuracy Assessments

The accuracy assessments for both 2010 and 2017 year is performed using two sets sampling datasets of LULC 2010 and LULC 2017 (Figure 5.1). First sample size was determined followed by the sampling technique. The whole process was done in ERDAS® where the tool accuracy assessment work according to the given number of sample size and sampling techniques. The tool generates the points on the classified map and stated the land cover class which were generated by the supervised classification method. The points were then evaluated with the reference data and stated the land cover type against each point which was stated in the reference data. Thus, the accuracy assessment tool generated an error matrix and then calculated overall accuracy, producer and user accuracy and kappa co-efficient.

5.3.1.1 Sample Size

Sample size is an important step for conducting the accuracy assessment of the remotely sensed data. In case of collecting ground truth data, the sample size could increase the survey cost. Thus, the analyst has to depend on a minimum sample size. However, it is always not possible to keep the sample size minimal in case of large area as there need a considerable amount of sample size to perform statistical validation. In remote sensing, often binomial probability theory is used to determine the sample size *N* for assessing the accuracy of a land-use classification map (Feller, 1968; Steel and Torrie, 1980; Fitzpatrick-Lins,1981). The following equations is called cumulative binomial probability distribution and expressed as:

$$N = \frac{Z^2 . p . q}{E^2} \tag{5.1}$$

Here, p is the expected percent accuracy, q is (100-p), E is allowable error and Z is equal to 2 (from the standard normal deviate of 1.96 for the 95% two-sided confidence level). If the above equation (Eq. 5.1) is solved for 85% accuracy with an allowable error of 5% then the expected number of samples is 203. However, the study decided to assess 280 samples for the reference data.

5.3.1.2 Sampling Technique

The selection of an appropriate sampling technique is also an important task for accuracy assessment. Improper choice of sampling technique could allow biasness in the error matrix resulting error in the degree of accuracy. Further, the sampling techniques may vary on the analysis techniques which would applied to the error matrix. Ginevan (1979) stated that the sampling technique chosen for the accuracy assessment should have three principles, firstly, the technique must have a low probability to accept a map of having low accuracy, secondly the technique must have high probability to accept a map of high accuracy and third, the technique should demand of having minimum number of samples of ground truth.

The researchers most often use random sampling and stratified random sampling techniques which have proved very reliable to get satisfactory results. Congalton (1988) conducted sampling simulations on three different study areas (agriculture, forest and pastureland) using simple random and stratified random sampling techniques which had given expectable results in all three cases. However, simple random sampling technique cannot be applicable always despite of having good statistical properties. Simple random sampling may cause under sampling or oversampling for a certain portion of the study areas and these may overcome by increasing the number of samples. However, as discussed it is always not feasible to increase the number of samples. Hence, stratified random sampling technique is preferred and recommended as this technique allows to select a minimum number of samples from each class of land cover (Lunetta & Lyon, 2004).

However, there is also pros and cons of stratified random sampling techniques. The problem could arise when collecting ground truth data using stratified random sampling technique. This technique could be impractical due to collect ground data at random locations in the study area. These random locations could be very difficult to access and could get the location sites after conducting the classification. Hence, this process increases the cost of the project as the test data cannot be collected with the training data collection and prolong the project lead time.

The study applied stratified random sampling technique for both 2010 and 2017 for evaluating the classified map with reference data. In addition, field survey was done for 2017 LULC map where purposive sampling also applied for additional 355 points. This sampling technique is applied as the study area is large to explore for the samples and it would be very expensive and time consuming.

Following the stratified random sampling technique, the sample points were generated proportionate to the distribution of each land cover classes in the image.

$$Number\ of\ samples\ from\ each\ stratum = \frac{No.\ of\ pixel\ in\ each\ stratum}{Total\ No.\ of\ pixels\ in\ the\ image} \times No.\ of\ samples\ required \quad (5.2)$$

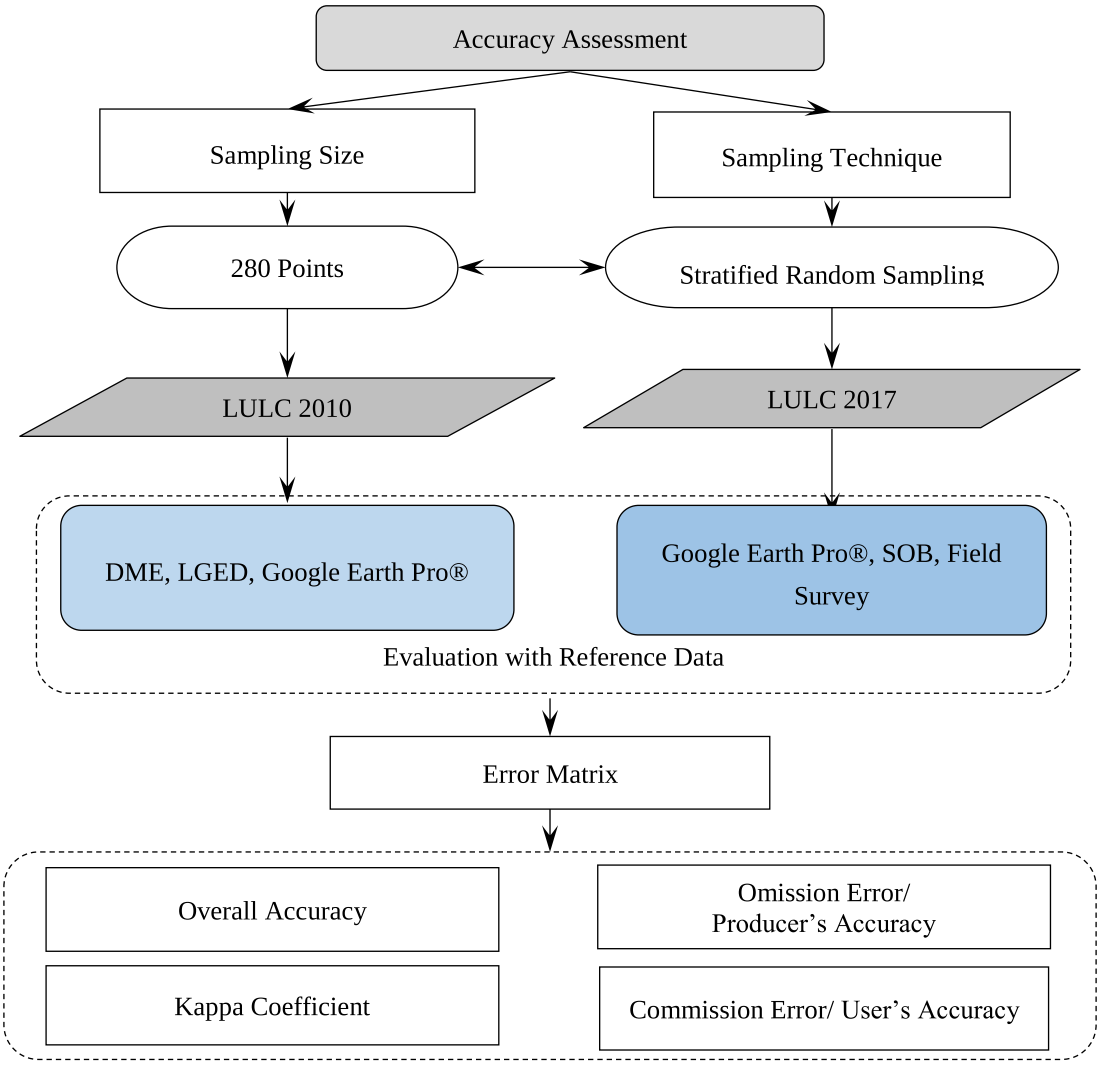


Figure 5.1 Flowchart for accuracy assessment.

5.3.1.3 Confusion Matrix

A tabular result of the comparison of the pixels in a classified image is known reference information **(Table 5.1)**. The main diagonal showing the correctly classified pixel samples.

Table 5.1 Example of error matrix for accuracy assessment.

Error Matrix	**Urban**	**Agri HL**	**Agri LL**	**Vegetation**	**Forest Sal**	**Water-bodies**	**Urban Transition**	**Row Total**
Urban	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$x_{1,5}$	$x_{1,6}$	$x_{1,7}$	x_{1+}
Agri HL	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$x_{2,5}$	$x_{2,6}$	$x_{2,7}$	x_{2+}
Agri LL	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$x_{3,5}$	$x_{3,6}$	$x_{3,7}$	x_{3+}
Vegetation	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$x_{4,5}$	$x_{4,6}$	$x_{4,7}$	x_{4+}
Forest Sal	$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$x_{5,5}$	$x_{5,6}$	$x_{5,7}$	x_{5+}
Water-bodies	$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$x_{6,5}$	$x_{6,6}$	$x_{6,7}$	x_{6+}
Urban Transition	$x_{7,1}$	$x_{7,2}$	$x_{7,3}$	$x_{7,4}$	$x_{7,5}$	$x_{7,6}$	$x_{7,7}$	x_{7+}
Column Total	x_{+1}	x_{+2}	x_{+3}	x_{+4}	x_{+5}	x_{+6}	x_{+7}	**N**

5.3.1.4 Overall accuracy

The overall accuracy is referred for basic accuracy assessment relates with total correct pixels and the total number of pixels in the error matrix. Thus, in the matrix, overall accuracy only takes the major diagonal values and eliminates the omission and commission errors. The overall accuracy can be expressed as:

$$= \frac{The\ total\ correct\ pixels\ (Sum\ of\ the\ major\ diagonal)}{Total\ No.\ of\ pixels\ in\ the\ error\ matrix} \tag{5.3}$$

Measures the accuracy of the entire image without reference to the individual categories

5.3.1.5 Producer's Accuracy and Omission Error

Producer's accuracy referred the ratio among the total number of correct pixel in a category and total number of pixel of similar category derived from reference data. Since the producer or the analyst of the classification would like to know how accurate the study area can be classified. The producer accuracy is calculated by following expression:

$$= \frac{\text{The total number of correct pixels in a category}}{\text{Total No. pixels of that category derived from the reference data}} \tag{5.4}$$

The statistic also contains error of omission which shows the proportion of the observed land covers of the study area that are not classified in the image. The producer's accuracy would be lower with the increase of the omission error (Banko, 1998).

$$Producer's accuracy\ (\%) = 100\% - error\ of\ omission\ (\%) \tag{5.3}$$

5.3.1.6 User's Accuracy and Commission error

The user accuracy is ratio of total number of correct pixel in a category and total number of pixels actually classified in that category. The expression of user accuracy is as follows:

$$= \frac{\text{The total No. of correct pixels in a category}}{\text{Total number of pixels actually classified in that category}} \tag{5.5}$$

The result is a measure of commission error, or error of inclusion. This measure, called the user's accuracy or reliability, is the probability that a pixel classified on the map actually represents that category on the ground.

5.3.1.7 Kappa Coefficient

The KAPPA is a discrete multivariate technique which is a part of accuracy assessment (Cohen, 1960). KHAT statistic is refer to as an estimate of KAPPA which is a measure of agreement. KHAT accuracy indirectly incorporates the off-diagonal elements as a product of the row and column marginal. Hence, KHAT accuracy is depended on the amount of error included in the matrix. The Kappa coefficient expresses the proportionate reduction in error generated by a classification process, compared with the error of a completely random classification.

$$K = \frac{N \sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k} x_{i+} \times\ x_{+i}}{N^2 - \sum_{i=1}^{k} x_{i+} \times\ x_{+i}} \tag{5.6}$$

where, k is the number of rows in error matrix, x_{ii} is number of observations in row i, column i, x_{i+} is the total number of observations in row i , x_{+i} is the total number of observations in column i, N is the total number of observations in matrix. A Kappa of 0.8 or above is considered a good classification; 0.4 or below is considered poor.

5.3.2 Post Classification Comparison

Post classification comparison is widely used change detection method due to its simply procedure and effective results. The method compares two classified images which produced independently (Singh, 1989). However, the two images of two time t_1 and t_2 must have the same coding of each land cover. Then the analyst can generate a change matrix which shows pixels of one land cover changed to another land cover from time t_1 and t_2. This helps the analyst to segregate the group of interest of land cover classification i.e. how many pixels of agricultural land have transformed into urban land. Post classification comparison technique is able to minimize the problem of normalizing due to have difference in sensor selection for two different dates. In addition, the method is also flexible for the geo-rectification of different images. Stow and the group (1980) had stated that if one single data image of Landsat is used for land cover classification, it may happen that the change map product of two Landsat classifications would have the same accuracies to the product of multiplying the accuracies of individual classification. Thus, the method could generate a significant amount of change indications due to an error in any image that used in change detection.

5.4 Results and Discussion

5.4.1 Accuracy Assessment of the LULC 2010

The classified map of LULC 2010 was used for the accuracy assessment. The overall accuracy of the map was found 82% and kappa co-efficient were found 0.79. The producer's accuracy was highest for the water-bodies and lowest for the forest sal, 100% and 54% respectively. Forest sal was misclassified mostly with the vegetation. The second lowest producer' accuracy was found in agricultural high land with 60%. The misclassification was done between agricultural fallow land and bare soil of urban transition. On the other hand, the user's accuracy was highest for the urban and lowest for the bare soil. Bare soil mostly misclassified with the fallow land of agriculture **(Table 5.2)**.

5.4.2 Accuracy Assessment of the LULC 2017

The accuracy assessment was done on LULC 2017 map, showed 84% of overall accuracy with kappa co-efficient of 0.8. In this map, the lowest producer's accuracy was found again in forest sal with only 54%. Here the most misclassification was occurred between vegetation and forest sal. The second lowest producer accuracy was found in urban with only 59%. The misclassification was mostly found between urban and urban transition **(Table 5.3)**.

Table 5.2 Confusion Matrix for LULC 2010

		Reference											
	LULC	Urban	AG-HL	AG-LL	Vegetation	Forest Sal	Water bodies	Urban Transition	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Classified	Urban	34	0	0	0	0	0	1	35	34	34	97.14%	100.00 %
	Agri high land	0	33	7	1	0	3	11	55	37	33	60.00%	89.19%
	Agri low land	0	0	44	0	0	1	0	45	57	44	97.78%	77.19%
	Vegetation	0	0	3	40	1	2	1	47	50	40	85.11%	80.00%
	Forest Sal	0	0	0	9	12	1	0	22	13	12	54.55%	92.31%
	Water bodies	0	0	0	0	0	26	0	26	33	26	100.00%	78.79%
	Urban Transition	0	4	3	0	0	0	43	50	56	43	86.00%	76.79%
	Overall Classification Accuracy =				**82.14%**				**280**	**280**	**232**		

Overall Kappa Statistics = **0.7939**

Table 5.3 Confusion Matrix for LULC 2017

		Reference												
	LULC	Urban	AG-HL	AG-LL	Vegetation	Forest Sal	Water bodies	Urban Transition	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Classified	Urban	35	0	2	0	0	0	1	59	38	35	59.32%	92.11%
	Agri high land	3	50	3	0	0	0	0	52	56	50	96.15%	89.29%
	Agri low land	0	0	35	0	0	0	0	45	35	35	77.78%	100.00 %
	Vegetation	1	0	2	66	0	0	0	72	69	66	91.67%	95.65%
	Forest Sal	0	0	0	6	5	0	0	5	11	5	100.00%	45.45%
	Water bodies	0	0	1	0	0	14	0	14	15	14	100.00%	93.33%
	Bare Soil	20	2	2	0	0	0	32	33	56	32	96.97%	57.14%
	Overall Classification Accuracy =	84.64 %							**280**	**280**	**237**		

Overall Kappa Statistics = 0.8136

5.4.3 Change Detection LULC of 2010 and 2017

The post classification comparison was successfully applied in urban studies due to its efficient performance to detect the rate of change, location sites and the phenomenon (Hardin and Jensen, 2007). Research showed the post classification change detection technique is able to generate more accurate result than the conventional methods (El-Hattab, 2016). The change matrix was applied in ERDAS® environment. Application of this tool resulted in a thematic map **(Figure 5.2)** detecting the areas where pixels of one class had changed by other classes and also the pixels, which were remained, unchanged. The attributes of the resultant map demonstrate the number of pixels for one class to another class. The transition matrix was done from the resultant map which illustrate the changes from one class to other classes **(Table 5.4).**

Table 5.5 shows the main changes that occurred related to urban and urban transition. The most significant changes occurred in urban transition. Approximately 97 km^2 of land has transformed from agricultural high land to urban transition. Agricultural low land also transformed to urban transition by 64 km^2 followed by vegetation by 48 km^2. Other changes were occurred due to urbanization where agricultural high land low land, vegetation and urban transition had changed to urban by 23km^2, 12 km^2 and 10km^2 and 33km^2 respectively. The urban transition and changed in urban took place mostly in the sub-districts as the capital city was occupied. Government, non-government organizations and privately owners has changed the lands for residential, industrialization and commercial purposes. However, this urbanization caused transformation of agricultural lands.

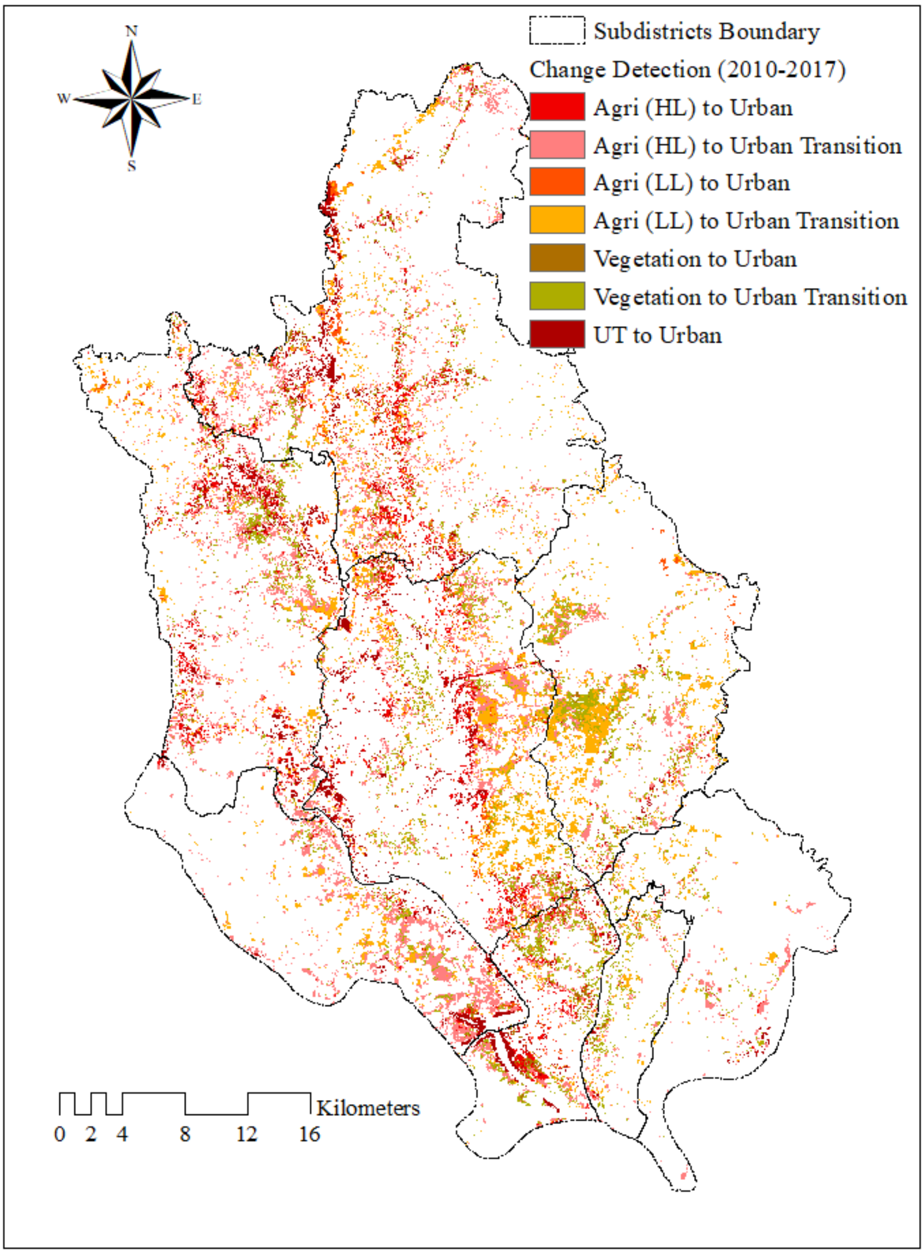


Figure 5.2 Major changes in the LULC from 2010 to 2017.

Table 5.4 Transition matrix for LULC 2010 to 2017.

		To 2017						
	LULC	Urban	Agri (HL)	Agri (HL)	Vegetation	Forest Sal	Water-bodies	Urban Transition
From 2010	Urban	172.52	4.21	4.21	6.26	0	2.84	35.31
	Agri (HL)	23.93	229.15	28.25	123.70	5.48	6.65	97.33
	Agri (LL)	12.44	62.77	173.53	49.35	0.71	18.53	64.29
	Vegetation	10.49	23.03	21.96	297.72	8.75	3.29	48.78
	Forest Sal	0.02	0.64	0.27	4.74	23.88	0.00	0.14
	Water-bodies	4.10	4.04	5.44	6.09	0.03	60.98	6.74
	Urban Transition	33.92	21.84	6.99	10.33	0.06	2.19	91.66

Table 5.5 Major changes in the LULC from 2010 to 2017.

From 2010	**From 2017**	**Area (km^2)**
Agriculture (High Land)	Urban	23.9256
Agriculture (High Land)	Urban Transition	97.3251
Agriculture (Low Land)	Urban	12.4398
Agriculture (Low Land)	Urban Transition	64.2888
Vegetation	Urban	10.4922
Vegetation	Urban Transition	48.7782
Urban Transition	Urban	33.9237

5.5 Summary

The accuracy assessments of the classified maps assisted to know the performance of a classified map. Since the resultant map could be used for further analysis, it was very important to know the accuracy level of the maps. In addition, the producer's and user's accuracy helped to know which land cover was sensitive for classification. This shows level of misclassification between two land covers. The study had used two sensors of Landsat 5 TM and Landsat 8 OLI. The both sensors TM and OLI has performed well for the land use classification. However, there were misclassification among the land covers. The Landsat TM was mostly sensitive for bare soil, fallow lands which resultant in misclassification for urban and agricultural lands. The sensor OLI was sensitive for the urban and urban transition. The urban areas were misclassified as bare soil. The post classification refinements had improved the accuracy level. The accuracy assessment was conducted for the developed LULC 2010 and 2017 maps. 82% and 84% overall accuracy were obtained for LULC 2010 and 2017, respectively. The kappa coefficient was found 0.8 for both LULC maps.

In spite of having misclassification among the land covers, the post classification change detection result showed a significant land loss of agricultural lands both in low land and high lands which had already transformed to urban areas or in a state of urban transformation. Vegetation lands also converted to urban areas. Total 46 km^2 of land had been transformed from agricultural lands and vegetation areas to urban areas during 2010 to 2017. A large area approximately 210 km^2 of land is now in the state of urban transition, which is a threat to agricultural low lands transformation. This may cause severe inundation and flash floods in the suburban districts and Dhaka City during heavy rainfall in monsoon seasons. The change detection assisted to find out the spatial pattern and temporal dynamics of the study area. Since the reliable data sources is still absence in Bangladesh and also difficult for the accessibility of the existing data base, remote sensing data sources is the best options for the scientific research and also for decision making. In addition, there are differences among the role and mission of different organizations of Bangladesh government related to the land resources. Thus, available database has some differences in their data. However, historical data is more difficult to assess and sometimes not available.

CHAPTER 6
Conclusions and Recommendations

6.1 Conclusions

Land use changes in the peri-urban could affect local food security and environment and eventually it could extend to regional level. However, sustainable cities are those who can sustain by using local resources and from its sub-urban areas. To achieve urban resilience, it is important to meet the local food demand, generating employments and protecting the environment. The unplanned expansion of industries and urbanization could provide employments, accommodations for the people but in the long run these could collapse the sustainable development process. Food security, environmental hazards could create more adverse challenge to recover the losses. To address these issues in terms of land use planning, suitability analysis for industries location selection could be an important tool for the local and regional policy makers. In addition, the land monitoring system by periodic land cover mapping and detecting the changes with the spatial approaches could provide an efficient legislation system.

The study took the opportunities of integrating approaches with GIS based MCDA and remote sensing to develop LSA model which can enable to execute a robust spatial analysis for locating suitable sites for industries. The model can combat with the environmental hazards and can protect the valuable agricultural lands. The designed model could implement stake holders opinions in the decision process which is an important factor to mitigate the socio-economic barriers and land conflicts with the local people. The micro level study in Savar with the developed model showed only 4% land is most suitable for expansion of industries. In addition, the research suggested to emphasis on compact economic zones rather than individual land sites for industries. The spatial model with an extension of decision rule found the area had four possible compact suitable industrial locations with minimum of 10 ha of lands. Further, the research also identified that Savar had experienced agricultural land use changes nearly 11-15% in one decade due to the unplanned industrialization and urbanization.

Furthermore, spatial validation analysis and time series data enabled to observe the land use changes associated with industrial facilities. In the micro-scale of study, it was observed 200 industries were constructed, transforming the agricultural lands, during the last decade. Unlike most developing countries, Bangladesh has a high population density. The lack of land use policies and environmental legislation and the transformation of agricultural lands to industrial areas increases the risk of losing agricultural lands. The micro-level study showed there is a need for monitoring the land use change in spite of having legal policy planning. Land use monitoring is an inherent part of the land use planning for the policy makers. Besides, researchers and stake holders also seek for a land use/land cover data for decision making. Since the land use monitoring is a retrospective nature study, past data is always needed. On this regard, remote sensing database has proven a reliable source for monitoring and developing past land use database. Due to open assess of the medium high-resolution satellite data, like Landsat launched in 1972, the land cover mapping has become easier for the researchers. Thus, the study focused further on land cover mapping of past years and to detect the changes on land use. The study attempted to increase the scale of the study area and hence had chosen other six sub-districts like Savar adjacent to the capital city Dhaka.

The LULC classification of 2010 and 2017 revealed that there was a significant increase of urban transition area by more than 100%. Urban land and vegetation had also increased by 14% and 20% in 2017 compare to 2010. However, there was a declined in both agricultural high and low land by 32% and 36% respectively. This is indeed a concerning state for land use management. The accuracy assessments of the two classified images were obtained 82% and 84% overall accuracy with 0.8 kappa coefficient. Thus, the classified images were acceptable for further analysis. The change detection of the classified images showed that approximately 210 km^2 land had transformed to urban transition and urban at the expense of degradation of agricultural high land, low land and vegetation. The urbanization and urban transition were spreading across the periphery of the capital city. Therefore, the research can be concluded as follows:

- A geo-spatial decision support system was developed integrating GIS and AHP as a multi-criteria Analysis for industrial site selection in a micro-scale at suburb areas of Dhaka City.
- The LULC analysis was performed using time series remote sensing satellite images in macro scale covering all sub-districts of suburban areas including Dhaka City for understand land use change dynamics.
- The LULC change detection was conducted in macro scale for all sub-districts of suburban areas including Dhaka City.

6.2 Recommendations

The research added a value in the land use planning for site selection and land use change dynamics by utilizing the supervised classification for satellite remote sensing for LULC monitoring. The growth of the urbanization by low esteeming the valuable agricultural lands, would be an indispensable challenge for food security and also for environments. The unsustainable land use management is one of the major cause for global climate change. Dhaka the capital city which is surrounded by the four major rivers has been faced numbers of serious flood for a long time. A large area of Dhaka and adjacent sub-districts are situated in the flood plain area. Most of the wetlands of Dhaka had been transformed to urbanization in the recent decades. Due to the improper planning and monitoring of the land use, water clogging has become a regular phenomenon for the city and surrounding area. Satellite remote sensing and GIS –based model developed in this research could serve as a key tool for monitoring the land use and also for the scientific research to deal with the issues regarding land use. The change detection is an important analysis for further land use planning for future generations. The following recommendations are proposed from this research for policy implications:

- ❑ The GIS and satellite remote sensing-based land use planning could be implemented to visualize publicly the transformation of lands use ease of legislation.
- ❑ Suitable site selection and enforced legislation must be consulted prior to industrial growth planning with environmental considerations.
- ❑ The rapid transition of lands from agriculture to urban causes agricultural land reduction and decrease of low land retention areas for rainfall. Thus, the agricultural low lands must be kept for rainfall retention area in suburban areas of Dhaka city.
- ❑ Urban transitional changes are a concern to balance the settlements growth. Satellite cities in the suburban areas of the Dhaka must be considered.
- ❑ The trends of the urban growth have the potential to simulate future land use and could help to formulate a sustainable land use planning.

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Appendix A

GIS-based MCA Modeling to Locate Suitable Sites of Industries in Suburb Areas of Bangladesh for Sustainability of Agricultural Lands

General Information

Name:	Occupation:
Position:	Organization:
Highest Education:	Age:
Email:	Date:

Analytic Hierarchy Process (AHP) for land use suitability analysis

Land use changes in the peri-urban could affect local food security and environment and eventually it could extend to regional level. However, sustainable cities are those who can sustain by using local resources and from its sub-urban areas. To achieve urban resilience, it is important to meet the local food demand, generating employments and protecting the environment. To address these issues urbanization and industrialization should be manage with proper legislation system. Spatial analysis with the help of GIS and remote sensing could help to find out the suitable locations for industries which would not affect the environment and the agricultural lands.

Therefore, land suitability analysis will be conducted with the help of GIS and AHP, a multi-criteria technique where a suitable site need to select for the growth of industry without affecting the existing agricultural lands. The following questionnaire has developed supporting the AHP technique, to acquire judgements of expertise from different fields.

Pairwise comparison for AHP technique is done by giving a score. Here, Saaty’s 9-point scale will be used for the study.

Table 1. Nine Point Scale for pairwise comparison.

Intensity of Importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement slightly favor one activity over another
5	Essential or strong importance	Experience and judgement strongly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgements	When compromise is needed

The nine-point scale range would be easier to understand with the color bar scale **(Figure 1).**

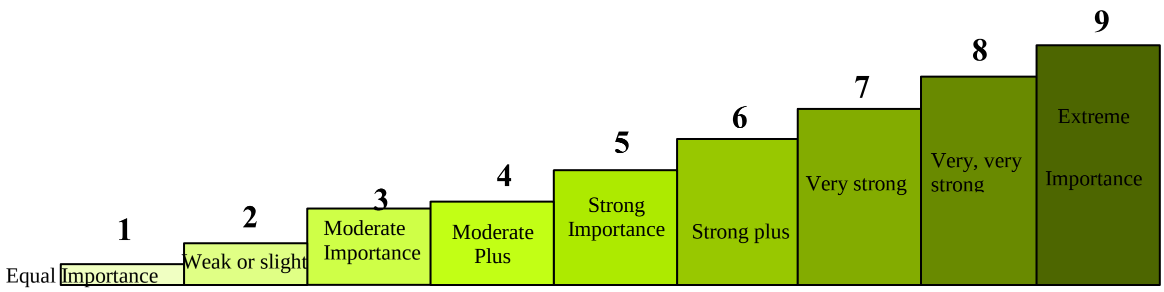

Figure 1. The relative importance of the nine points in color bar.

Example to fill- up the questionnaire for pair-wise comparison

According to the nine-point scale **(Table 1)**, the pairwise comparison table is designed **(Table 2)**. Left side of the "equal" is to express which one is "more important" than the other one and right side of the equal is for expressing which one is "less important" than another criterion. 1 to 9 points are for expressing intense i.e. "how much more" or "how much less" is important while comparing between two criteria.

If C1 is very strong influencing criterion to select suitable lands for industry than C2, then have to circle 7 in the left side of “more important than” or If C2 is less important than the criterion C3 moderately, than have to circle 3 in the left side of “Less importance than” or

If C3 has the equal influence compare to C1, then need to circle 1 in the middle.

	Factor weighting score																	
Criteria	More importance than								Equal	Less importance than								Criteria
C1	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	C2
C2	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	C3
C3	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	C1

Table 2. Example of a pairwise comparison matrix.

Part 1:

The criteria have selected from the initial survey and from previous studies. Please give your opinion to know how much these criteria influence to select suitable locations for industry.

Table 3. Pairwise comparison matrix of criteria for land suitability analysis for industry.

		Criteria weighting score																	
No	Criteria A	More importance than								Equal	Less importance than								Criteria B
1	Proximity to major roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from Settlements
2	Proximity to major roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Proximity to local roads
3	Proximity to major roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from rivers
4	Proximity to major roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from water bodies
5	Proximity to major roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Agricultural lands

6	Proximity to major roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Flood flow zones
7	Distance from Settlements	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Proximity to local roads
8	Distance from Settlements	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from rivers
9	Distance from Settlements	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from water bodies
10	Distance from Settlements	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Agricultural lands
11	Distance from Settlements	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Flood flow zones
12	Proximity to local roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from rivers
13	Proximity to local roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from water bodies
14	Proximity to local roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Agricultural lands
15	Proximity to local roads	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Flood flow zones
16	Distance from rivers	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Distance from water bodies
17	Distance from rivers	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Agricultural lands
18	Distance from rivers	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Flood flow zones
19	Distance from water bodies	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Agricultural lands
20	Distance from water bodies	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Flood flow zones
21	Agricultural lands	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Flood flow zones

Part 2:

Fifteen factors and five constraints under the criteria have selected which need to give a score to support land suitability analysis in GIS. The score range for the factors is 1 to 10 where the even numbers are referred to a suitability ranking **(Table 4).** In addition, constraints are treated as restrictions i.e. "Not suitable" for consideration and thus should score as "0". However, respondents could give their own judgement based on their specialization or relative reference.

Table 4. Suitability scores.

Score	Suitability Ranking
0	Not suitable
2	Suitable but avoided
4	Least suitable
6	Less suitable
8	Moderately suitable
10	Most suitable

Table 5. Suitability score ranking according to expertise.

No.	Name of the Criteria	Factors/Constraints	Classified	Score
1	Proximity to major roads	0-100 m	Constraints	
		100-500 m	Factors	
		500-1000 m	Factors	
		1000-1500 m	Factors	
		1500-2000 m	Factors	
		>2000 m	Factors	
2	Proximity to local roads	0-50 m	Constraints	
		50-200 m	Factors	
		200-400 m	Factors	
		>400 m	Factors	
3	Distance from rivers	0-500 m	Constraints	
		500-750 m	Factors	
		750-1000 m	Factors	
		>1000 m	Factors	
4	Distance from water bodies	0-100 m	Constraints	
		>100	Factors	
5	Flood flow zones	Flood Flow Zone	Factors	
		Non-Flood Flow Zone	Factors	
6	Distance from settlements	0-50 m	Constraints	
		>50 m	Factors	
7	Agricultural lands	Agri-land	Factors	
		Non-Agri-land	Factors	

Part 3: If you have any suggestions or comments, please feel free to write.

Appendix B

Expert's references for the prioritizing criteria for AHP and scoring of factors and constraints

A group of Expert's opinions were taken to make consistence on the judgement of pairwise comparison of the criteria to execute the AHP method to know the priority weighting of each criterion. Expert's suggestions were taken to maintain the consistency on the judgements which ensure the consistency of the methodology of the study to conduct the land suitability analysis. In addition, scoring for the factors of criteria were also done by the Expert's opinions. The Experts were chosen from the field of GIS, Civil Engineering and Environment.

No.	Expert Name	Specialist/Profession/Higher Education
1	A	Civil Engineer, Institute of Water Modelling, Bangladesh
2	B	Associate GIS & RS Specialist, Institute of Water Modelling, Bangladesh.
3	C	Project Director, Civil Engineering, Local Government Engineering Department.
4	D	Sr. Assistant Engineer, GIS, Local Government Engineering Department.