CULTURAL AND ENVIRONMENTAL TRANSITION AND TRANSFORMATION OF TWO SOUTH ASIAN CITIES: DHAKA AND KOLKATA

By

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ABSTRACT

South Asian cities have entered the group of fastest growing megacities in the world in recent times. Two megacities, Dhaka in Bangladesh and Kolkata in India across borders, have experienced similar political changes in the 20th Century, which have molded and transformed the cities, culturally, demographically and environmentally over the past century. The three major political events have induced migrations within and beyond borders between the two countries. The transformation of the shape and form of the two cities over time had profound impact on the local environment. Traffic congestion, air pollution, increased whereas natural landscapes decreased. Thus in this study, comparison of Dhaka and Kolkata have been performed in three steps - the political events and its influence on urban growth and policy; the impacts of urban growth on land cover and local environment in terms of particulate matter pollution; and correlation between land cover change, environmental impacts and peoples accessibility to healthy environment.

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LIST OF ABBREVIATIONS

NDVI	Normalized Difference Vegetation Index
NDBI	Normalized Difference Built up Index
NDWI	Normalized Difference Water Index
DMA	Dhaka Metropolitan area
KMA	Kolkata Metropolitan area
KMC	Kolkata Municipal Corporation
DIT	Dhaka Improvement Trust
DAP	Detail Area Plan
NATMO	National Atlas and Thematic Mapping Organization
CART	Classification and Regression Trees
GEE	Google Earth Engine
TOA	Top of Atmosphere
AOT	Aerosol Optical Thickness
NAQS	National Ambient Air Quality Standard
PM	Particulate Matter
CASE	Clean Air and Sustainable Environment
ETM	Enhanced Thematic Mapper
OLI	Operational Land Imager
AQI	Air Quality Index
OGD	Open Government Data
WBPCB	West Bengal Pollution Control Board

CHAPTER 1: INTRODUCTION AND STUDY AREA

1.1 Introduction

Urbanization is proven to be one of the most instrumental factors in shaping social growth and natural development (Li et al. 2012). Worldwide urban population exceeded rural population in 2007. Asia and Africa are expected to see the maximum urban growth in the coming years (Griffiths et al. 2010). Besides development, urbanization also incurs some economic and environmental losses especially in the developing countries due to the inefficiency of urbanization process (Bertinelli and Black, 2004). Urbanization and globalization are the causes behind the emergence of mega cities, resulting in the weak functioning of the cities (Griffiths et al. 2010).

Urban areas occupying 10 million people are regarded as mega cities (UNICEF, 2012). Numbers of megacities are increasing at a rapid rate around the world. In 1975, there were only 3 megacities and among them, Tokyo were the only one outside America. In 2009, out of 21 megacities across the world, 9 were from Asia (UNICEF, 2012). In 2018, there were 7 cities from Asia among 10 largest mega-cities across the whole world (UN, 2018). The factors that triggered the growth of the megacities are employment opportunity, division of labor, centralization and large-scale industrialization (UNICEF, 2012). Aguliar, Ward and Smith Sr (2003) found that, the form and shape change over time. At present mega cities are expanding their domain to nearby small towns and peripheries of the cities instead of going for compact development. Cities in developing regions especially in South Asia have hugely experienced urban sprawl, once which was the characteristics of the developed countries of North America too (Moghadam and Helbich, M, 2013).

The formation and expansion of megacities have created immense pressure on the infrastructure and environment of the urban core as well as the peripheries of the cities. Demand of land for industrial, commercial and institutional activities not only affects the urban ecosystem but also increases other associated land uses too (Aguliar, Ward and Smith Sr, 2003). These landcover transformations into impervious surfaces are also the root cause for urban heat island effect and environmental degradation (Kalnay, and Cai, 2003). Vegetation and agriculture, which are gradually disappearing in urban areas, are the prime elements to increasing the minimum temperature and decreasing of maximum temperature (Kalnay and Cai, 2003). Besides that, urbanization factors namely population growth, density, burning fossil fuels, transportation intensity etc. are responsible for decreasing the air environment quality (Wang et al. 2011).

Dhaka and Kolkata are two of South Asian mega cities, having similar languages, cultures and lifestyles, situated across borders. Dhaka is the capital of Bangladesh and Kolkata is the capital of the state of West Bengal in India. Bangladesh's economy, education, commerce, industry etc. are highly centralized in Dhaka (Siddiqui et al. 2016). The centralization of the major activities and high density have a demand on the land cover to be changed. Kolkata, once the capital of British India was the first city in India to have one million people and has experienced rapid growth till 1971 (Yadav and Bhagat 2014). Now the cities have expanded to include the suburban settlements around the main city. The growth of both cities has also seen increased urban infrastructures, water scarcity and air pollution which compromises healthy livable conditions (Ahmed, Hasan and Maniruzzaman, 2014).

The pertinent problem associated with urban growth in these two South Asian megacities have given rise to the following research questions:

1. How has major political events before and after independence of the two countries, Bangladesh and India, impacted the growth of Dhaka and Kolkata? How the land cover has been changed and what is the pattern of change for the two cities?
2. What is the impact of land cover change on air pollution of Dhaka and Kolkata as they have grown bigger? How the air pollution is correlated with the land covers (Greenspace: Normalized Difference Vegetation Index (NDVI), Built-up Area: Normalized Difference Built-up Index (NDBI), and Waterbody: Normalized Difference Water Index (NDWI)) from continued urban growth in Dhaka and Kolkata?
3. What are the lower polluted areas? What is the accessibility to those areas from building blocks and how this accessibility is correlated with people's demographic and socio-economic characteristics?

This research has also some scope for further study. This study tries to find how the urban areas of these two cities has changed politically and geographically. How these changes have shaped the cities environment comprehensively how these changes have an influence on people's accessibility to healthy environment. The significance of this research is, it worked on temporal urban transformation of these cities and at the same why and how these changes are important for the humans. This research is important for researchers want to conduct further study on urban expansion, environmental pollution, urban residents' exposure to healthy environment and urban accessibility and connectivity. This research will also complement urban planners and policy makers decision of providing more natural landscapes considering urban livability of these cities.

1.2 Location of Study Areas:

1.2.1 Dhaka, Bangladesh

Dhaka is one of the six South Asian mega cities having a population over 16 million according to 2010 housing survey of Bangladesh (Kamruzzaman, 2019). The capital city is also the 3rd most densely populated cities in the world (World Atlas, 2018). The country's economy, education, commerce, industry etc. are highly centralized in Dhaka (Siddiqui. K et al., 2016). Rural-urban migration is a common phenomenon in Dhaka where 39.36% of total population of the city came from rural areas (Chaudhary, 1978). To accommodate these people, a large portion of land is being converted to residential areas with over 40% land used as informal settlements (Dewan and Yamaguchi 2009). Moreover, establishments have been built for commercial and industrial purposes to fulfil the need of employment for the influx of people. From 1975 to 2003 waterbodies (2.3%), wetland (9.7%), cultivable land (8.6%) and vegetation (6.2%) all have been significantly reduced in the city. The two increasing land cover types by percentage are built up and land fill (Dewan and Yamaguchi, 2009).

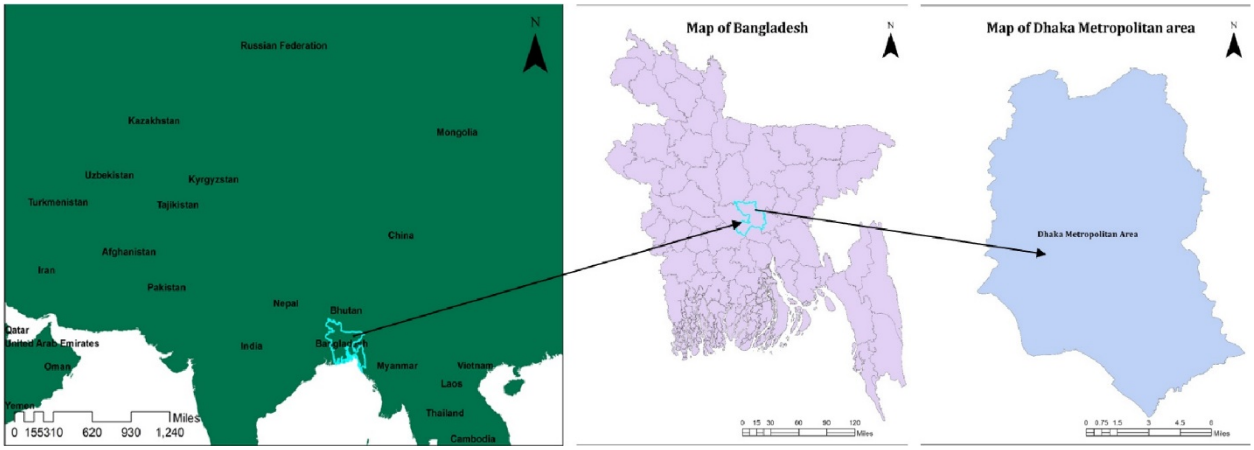


Figure 1.1: Study Area: Dhaka (OCHA, 2015)

With this rate of decrement, vegetation and waterbody will be not be more than 4% and 5% respectively by 2020 whereas the built-up area will occupy 46% of the total Dhaka city land (Islam and Ahmed 2012). With this estimate, it is high time to identify the land cover changes and its impact on other aspects of urban environment.

1.2.2 Kolkata, India

Kolkata is the capital of the state of West Bengal in India. East side of West Bengal shares the Indian country boundary with Bangladesh. The city has a humid and wet climate with a larger pre-monsoon and monsoon period (Sharma et al. 2015). Kolkata has number of administrative areas. The core city has a boundary of 200 km^2 and occupies about 4.5 million people (Mukherjee, Bebermeier and Schutt, 2018). Kolkata Municipal Corporation (KMC) area is situated on the eastern bank of the river Hooghly. KMC (205 km2) contains the center of Kolkata Metropolitan Area (KMA) and corresponds to the urban agglomeration of the city of Kolkata. The industrial hub and the port, both attract migrants not only from eastern India but also from neighboring countries of eastern part of South Asia (Mukherjee et al. 2018). Kolkata metropolitan area (KMA) contains the core city, suburbs and some other places which totals 1851.41 km^2 (Bhatta, 2012). The area has a population not less than 15 million. It makes the city the 3rd largest among India (Mukherjee, Bebermeier and Schutt, 2018). With the increase in demography, the city also expanded geographically followed by urban sprawl along the rural roads outside the downtown of the city (Sharma et al. 2015). The city grew naturally till 1947. After 1947, the growth started at a very fast rate as more people started coming to the city for employment. The partition of the Indian subcontinent and influx of people from Bangladesh were other major reasons behind that. From 1947 to 1990, the spatial growth was about 30 km^2 (Mitra et al.2012)

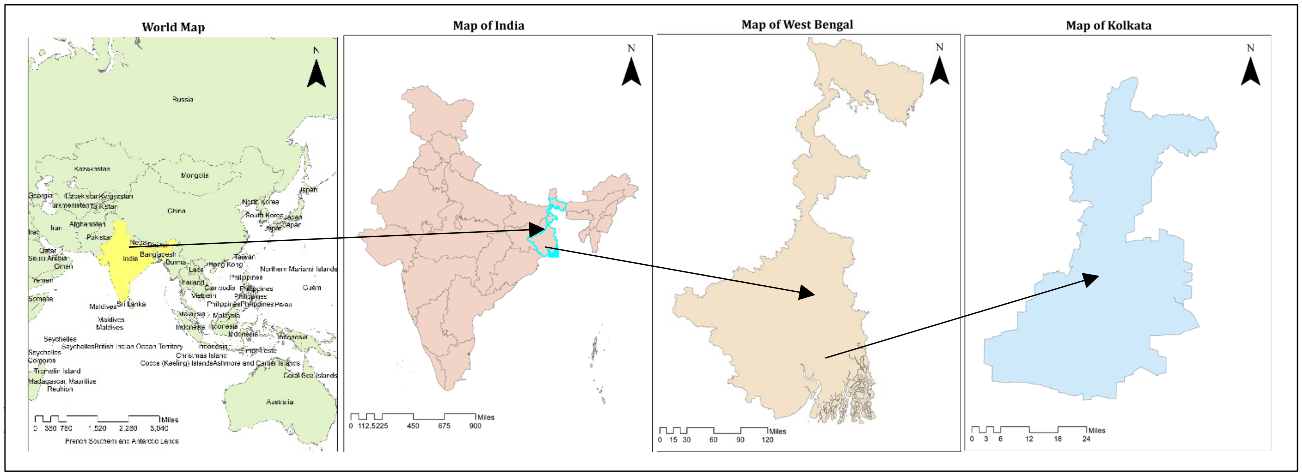


Figure 1.2: Study area: Kolkata (Center for Geographic Analysis, Harvard University)

During 1990-2000, the growth rate was 192.55% and in the next decade it became 0.02% (Bhatta, 2012). Bhatta (2012) also found that the growth rate between 2001 – 2010 was lowest compared to other time periods. This happened due to the spatial variation in the built-up concentrations in different geographic location within the city. Some areas are highly concentrated such as in south Kolkata, and newly developing areas in east Kolkata. This increasing growth rate happened at a faster rate than gradually. Previously developed areas have low growth rate. When the newly developed areas reach to saturation point, the growth rate declines dramatically (Bhatta, 2012).

CHAPTER 2: HISTORICAL URBAN GROWTH AND LAND COVER CLASSIFICATION

2.1 Historical Urban Growth of Dhaka And Kolkata

Dhaka and Kolkata cities have undergone the brunt of several major political events from the beginning of 20th century. These political events shaped the city's boundaries, ideology, culture and political scenarios again and again. These political events have also impacted the cities land use, land cover, economic activity, form and infrastructure.

2.1.1 Major Political Events in Twentieth Century

2.1.1.1 Partition of Bengal (1905-1911)

In the British period (from 1772 to 1911), Kolkata was the capital of British India. Kolkata, known at that time as Calcutta, was also the principal city for the undivided Bengal which included West Bengal, Assam, Orissa, Bihar, Tripura and East Bengal. The government found it difficult to rule these large areas from Kolkata. The other cities and areas of the vast presidency (state) also got less attention and benefits from the government in terms of development activities and opportunities. On 19th July 1905, government of India declared the consent of setting up new province of 'Eastern Bengal and Assam' comprising Chittagong, Dhaka and Rajshahi divisions, Hill Tippera (present Tripura), Malda and Assam. The formal proclamation came on the first of September and Bengal was partitioned on 16th October of 1905. Dhaka became the capital of the new province (Sarkar, S, 1973). After long protest from masses, the government decided to annul the partition and it was on effect from 12th December 1911. After 1911, both Dhaka and Kolkata lost their significance. Dhaka lost the crown of capital of a province. Similarly, the capital of British India was also shifted from Kolkata to Delhi. (Saxena, 1987).

2.1.1.2 Indian Independence and East-West Pakistan (August 1947)

After the cancellation of the Bengal partition in 1911, the relation between Hindus and Muslims deteriorated. In 1946-47, when Britain was on the verge of leaving Indian Subcontinent, communal tension between Hindus and Muslims gained much prominence. Some key questions were considered, firstly whether they want to keep the united Bengal instead of being two different provinces of India and Pakistan. Secondly, if the whole of Bengal remained within India then the separate electorates would've been the preferable solution. Third, whether they can endure the dominance of Muslim League (political party for Muslims in Indian subcontinent) in the united Bengal in India. So, partition of the province (state) was the most desirable solution for each religious group's dominance in provincial government and central government as well (Roy, 2009).

After continuous and devastating communal riots between Hindu and Muslim in 1946 followed by unstable political conditions, partition became inevitable. So, Bengal legislative assembly met to decide the future of Bengal on 20th June 1947. The administrative power from the British was then transferred the administrative power to India and Pakistan on 14th and 15th August of 1947 respectively. The province as well as the whole country was divided by Radcliff Line, a line which divided India and Pakistan (Mukherjee, 1968).

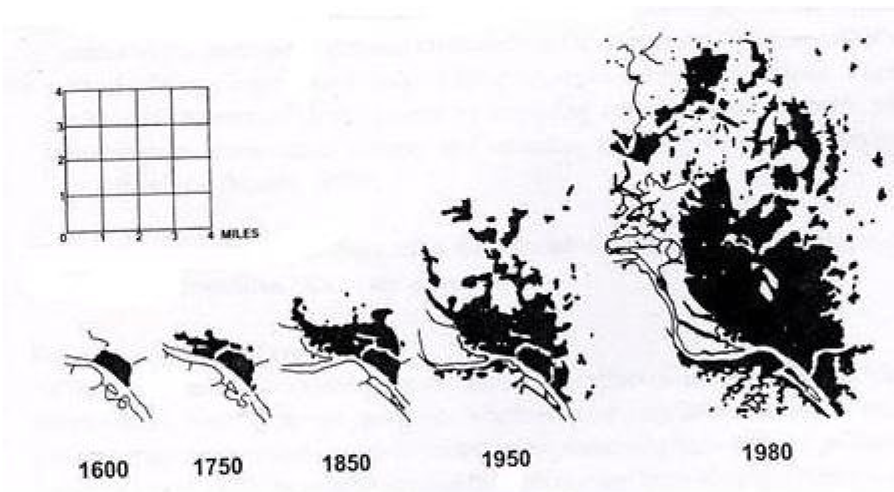
2.1.1.3 Independence of Bangladesh, 1971

After 1947, Dhaka became the capital of East Pakistan. East and West Pakistan (present Pakistan) were separated from each other by more than 1,000 miles with distinct differences in language, cultural heritage, physical appearance and climate. The only common thing between them was the religion. East Pakistan was treated as a province of Pakistan and the administrative power, foreign ministry, finance ministry, defense ministry was controlled from West Pakistan. After the birth of East Pakistan, most of the people in East Pakistan had high aspirations of a new state. Though East Pakistan had 15% of the total area of the country it had majority population of the whole Pakistan (Bangladesh Documents, 1971-73). After those incidents, the liberation war happened in 1971. During the liberation war of Bangladesh, a lot of people from East Pakistan fled to India to save their lives from the massive killings of Pakistan military (Bangladesh Documents, 1971-73).

2.1.2 Historical Growth of The Cities

2.1.2.1 Dhaka City, Bangladesh

Dhaka city became an important city in 1608 when Islam Khan became the subedar (administrator) of the city appointed by Mughal emperor and it is termed as the birth year of prominent Dhaka (Kabir and Parolin, 2012). Dhaka became an important city after being the capital of Bengal province in the Mughal period (1600 to 1700).



Islam khan, the then subedar of Bengal made Dhaka his capital in 1610. After the Mughal period Dhaka entered the British period when the city lost its importance and development was reduced.

Figure 2.1: Historical expansion of Dhaka (Ahmed et al. 2014)

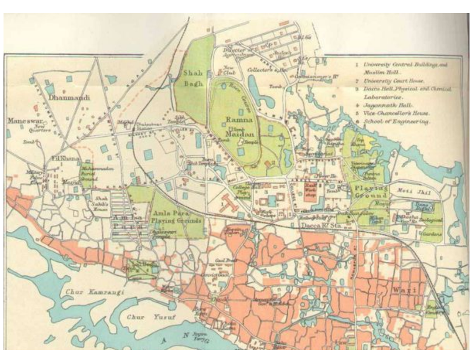


Figure 2.2: Dhaka city in 1924 (Murray, 1926)

Development plan of Dhaka by Sir Patrick Geddes in 1906 is the only development steps during the British period (Kabir and Parolin, 2012). After becoming the capital of East Pakistan in 1947, Dhaka experienced rapid change. The city started to expand towards the north, and the northern part was called the new Dhaka. Dhaka Improvement Trust (DIT) was established in 1956 to develop the plan of the city. DIT has developed 4 new major urban area named Gulshan.

Model town, Banani, Uttara and Baridhara model town of the city (Kabir and Parolin, 2012). Like the DIT initiative, the city developed other planning projects and reports since the beginning of 19th century like Dacca Town Planning Report (1917), East Pakistan Planning Sub-Committee

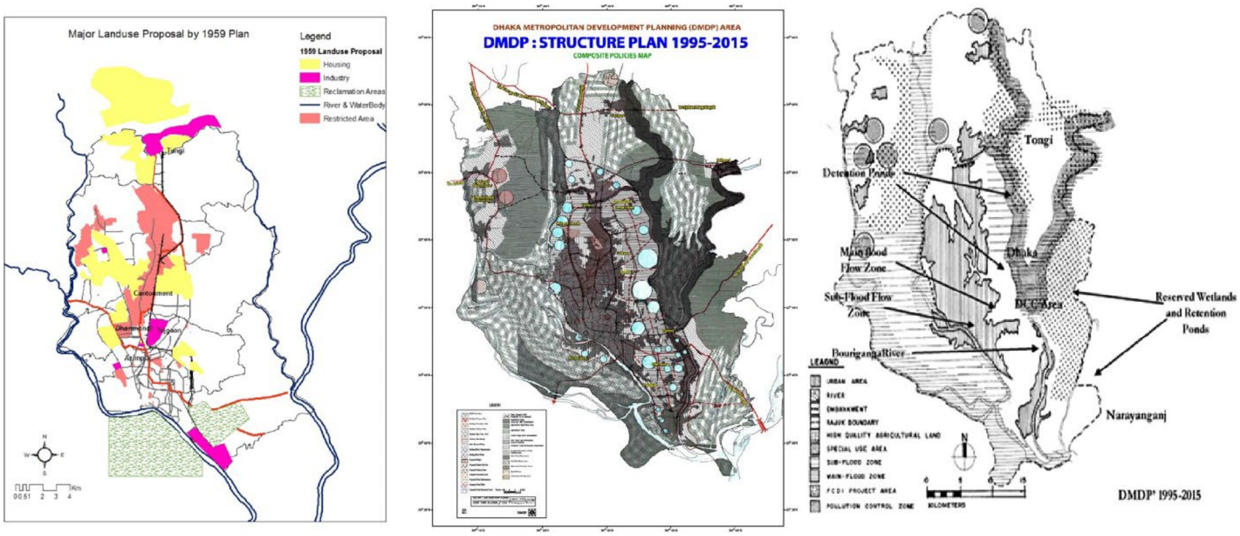


Figure 2.3: Dhaka Master Plan in i) 1958, ii) 1995 and iii) 2016) (RAJUK, 2020)

(1948) and Dacca Master Plan (1959). The City Development authority of Dhaka, named RAJUK, initiated some projects demarcating the area of the city. The first one named ‘Dhaka Metropolitan Area Integrated Urban Development Project’ came in 1981. Then RAJUK launched the project of ‘Dhaka Metropolitan Development Plan’ in 1995. In 2015 RAJUK started the Detail Area Plan (DAP) project including the suburban areas of the city (Kabir, and Parolin, 2012).

2.1.2.2 Kolkata City, India

Kolkata city, formerly known as Calcutta, has controversy regarding its birth. The year 1690 is considered as the birth year of Kolkata referenced from the maps available. The establishment of the city is related with the establishment of East India Company during 1600. In 1690, Kolkata began with three villages (Kolkata, Gobindapur and Sutanuti) along river Hooghly as a trading post by Job Charnock and then Fort William was established in 1698 (Yadav and Bhagat, 2014). The first plan of Kolkata by Mark Wood was published in 1792. It featured division of the town according to the European and native inhabited areas. The developed European colony areas around the 'Great Tank' extended along the Bytaconnah or Bow Bazar street, and along present-day Lenin Sarani both ending at Mahratta ditch (NATMO, 2010). Figure 2.4 shows that, during 1893, Kolkata was only concentrated on the eastern bank of Hooghly river and very small areas were contained within its boundary.

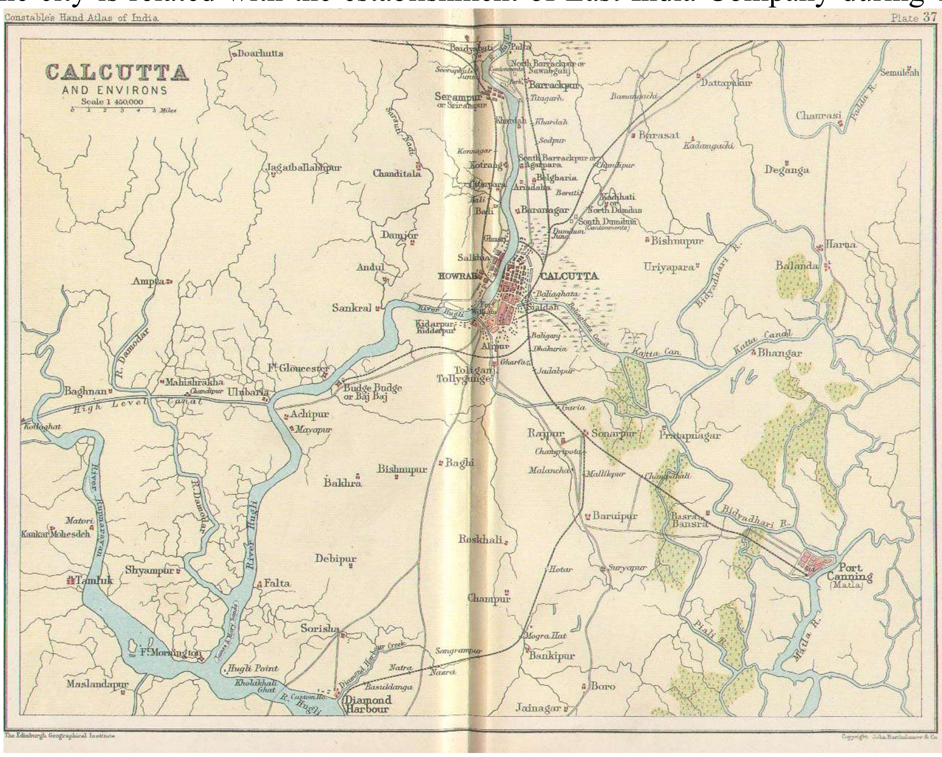


Figure 2.4: Kolkata in 1893 (Pritchett, 2020)

After 1793, Kolkata started to become an administrative center. The treasury of British East India Company was established in Kolkata. Real power and authority moved from the Nawab of Bengal to the Company, so the center of power shifted from Murshidabad to this town. Several educational institutions, foundations, and clubs were established for the educated middle class. During 1793-1856, built up areas surrounding the 'Tank square' increased substantially. The townscape which developed during the period had a lot of similarity with London (NATMO, 2010).

Figure 2.5: Map of Kolkata in i) 1906, ii) 1914 and iii) 1927 (India Water Portal, 2010)

The design, architecture and planning of Kolkata were highly influenced by the planning and design of the capital of British empire like The grid-iron pattern of roads, squares, the strand along the river, names on the street like Park street or Russel street, architecture of buildings, open spaces like Esplanade (NATMO, 2010).

The development process continued in 20th century as well. Kolkata became the center of initiating development activities within India. Figure 2.5 shows the temporal expansion of Kolkata from 1906 to 1927. The light green portion of the image was greenspace (Maidan) and the red portion was inner city. One-mile scale of the image represents the smaller boundary of the city. the images show that, during that British period, the city's urban areas have been developed in a grid iron pattern along the Hooghly river on the eastern bank. The images show some temporal expansion on the western part of the Hooghly river in these time periods. Introduction of electric trams (1902), and aero plane (1910), establishment of Indian Broadcasting Company (1927), building of Victoria Memorial (1929) and construction of Howrah Bridge (1941) were some of the significant developments in Kolkata. Some of the major activities of the freedom movement also initiated and concentrated in the city at that time (NATMO, 2010).

Figure 2.6 shows expansion of Kolkata from its early establishment. It shows that the growth rate was slower in the early periods and it accelerated after 1793 when Kolkata became the capital of British India. The growth accelerated again after 1947, after the independence of India. After the independence, the city became the capital of West Bengal state and the city started to grow dramatically (NATMO, 2010)..

Figure 2.7 shows the urban growth of the city in 1952 and 1972. In 1972, Bangladesh became independent and the migration of Bangladeshi people had some influence over the city's expansion in this time period.

Presently the Kolkata agglomeration has an area of 1851.42 sq. km including both sides of Hooghly River, the levee of the river and the marshy tract of the east. During the last decade, Kolkata have experienced rapid development by changing the proper city and adding the suburban areas. Several new roads, flyovers and third bridge over Hooghly river have accelerated the pace of development and made the communication with Delhi and Mumbai easier. These initiatives have triggered the city growth and responsible for land use change of hundreds of acres of agricultural land which have transformed into uses other than agriculture and vegetation (NATMO, 2010).

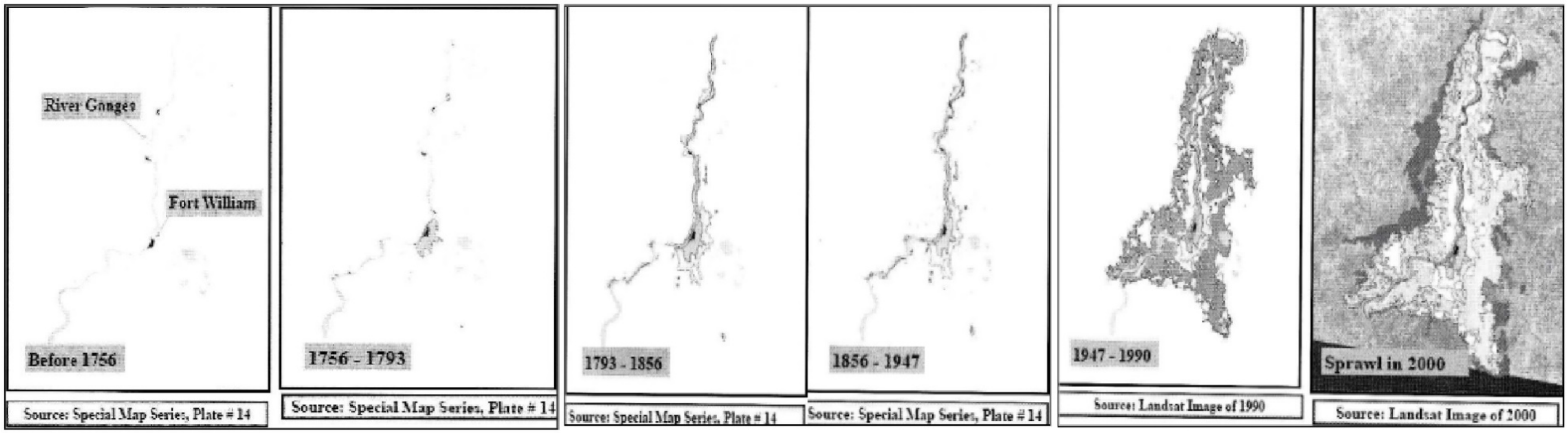


Figure 2.6: Urban growth of Kolkata from 1756 to 2000 (Source: Mitra et. al. 2012)

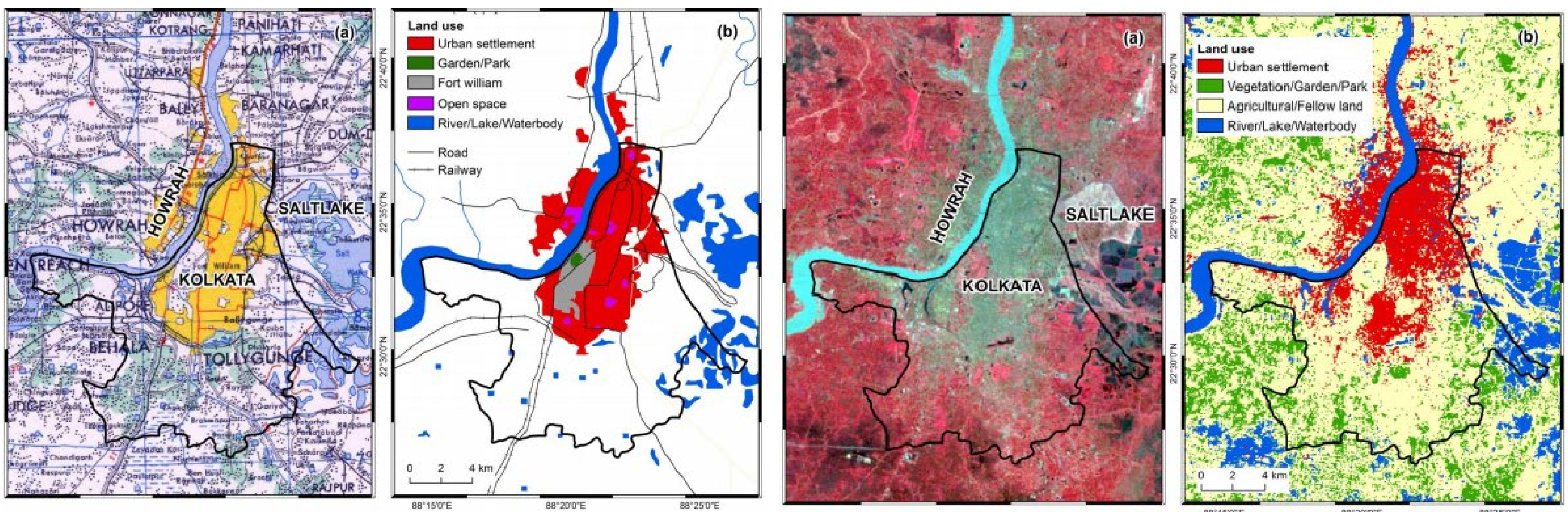


Figure 2.7: Urban growth of Kolkata from 1952 to 1972 (Mahata et al. 2017)

2.2 Land Cover Change of The Cities

Land use land cover change has both direct and indirect influence on urban sprawl especially in developing countries (Mosammam et al. 2017). Decrease of vegetation and agricultural lands, their productivity and several climate impacts (Mosammam et al. 2017). Land cover change is considered a key factor for global environment and climate change. It has noteworthy influence on global and regional scale policy and planning decisions too (Oyugi, Odenyo and Karanja, 2016). Some studies say that, land cover change has profound impacts on precipitation, increases carbon dioxide (CO^2) and other pollutants, modifies the microclimate, change in vegetation dynamics etc. (Mahmood et al. 2010). To understand this climate change, land surface temperature (LST) is used as an indicator (Feddema et al. 2005). The surface temperature depends on the distribution of land covers based on area's geographical location, atmosphere and anthropogenic factors (Feddema et al, 2005). Several studies say that urban areas across the globe is experiencing rapid changes in land use and land cover resulting in changes of land surface temperature too (Carlson and Arthur 2000). Due to unplanned urbanization these areas are suffering from increasing pollution and changes in the climate with no specific plan in hand to cope with them. (Carlson and Arthur, 2000).

The formation and expansion of megacities have created immense pressure on the infrastructure and environment of the urban core as well as the peripheries of the cities. Demand of land for industrial, commercial and institutional activities not only affects the urban ecosystem, but also impacts associated land covers and land uses contributing to urban sprawl (Aguliar, Ward et al., 2003). Suburban and peri-urban areas are losing natural landscapes, protected areas, flood flow zones, agricultural areas and waterbodies. Loosing of these landcovers don't impact the environment instantly rather provide more economic value from converted land uses making the transformation worthy. Gradually, these transformations take massive toll on the habitat as they cannot work as a barrier to natural hazards and calamities (Yuan et al., 2005). The lost agricultural lands threaten the availability of required food supply which traditionally came from the suburban areas of the city (Lopez et al., 2001). As a result, catchment area of the city's demands for food is becoming larger gradually (Haregeweyn et al., 2012). Decreasing of natural places also affect the air quality of the city. These landcover transformations into impervious surfaces are also the root cause for urban heat island effect and environmental degradation (Kalnay, and Cai, 2003).

Vegetation and agriculture, which are the prime elements to increasing the minimum temperature and decreasing of maximum temperature, are gradually disappearing in the fringe and suburban areas of major cities (Kalnay and Cai, 2003).

Multi-temporal LULC (Land Use Land Cover) classification has become a popular method for land cover classification in recent times (Kantakumar and Neelamsetti, 2015). In Dhaka, several researches have been conducted using post classification method. In most of those research's, only 4 classes have been selected which are Waterbody, Vegetation, Built Up area and Barren Land. Wetlands and agricultural lands are also a major part of Dhaka city though these 2 land covers are decreasing dramatically (Ahmed et al., 2013). These land covers are most often merged with other land covers like waterbody, vegetation and barren land. So, identification of these land covers is challenging and time consuming. There are several sophisticated methods of classifying land covers for example Very High-Resolution Imagery (VHRI), Normalized Difference Vegetation Index (NDVI), Normalized Burn Index (NBR2), Liquid Surface Water Index (LSWI), etc. (Oliphant et al., 2019).

Training sample data is an instrumental part for supervised land cover classification and the accuracy of the classification mostly depend on it (Abdi, 2019). Training data are those based on which the classification algorithm works and run the classification taking the range of spectral signatures of the training samples. As this study has classified six classes and differentiated some classes which have very close range pixel values, selection of training data was also a very necessary part of this study. For resource constraint this paper employed simple random sampling method to select the training data. Land covers referenced from previous images and google earth timeline images were used to select the training data. The freely available highest resolution images for these cities is Landsat which provides 30 m*30 m image. For selection of training data, very high-resolution images or hyper spectral images are a better option. Field survey is also an efficient option for selecting training data where very high-resolution images are not available. One of the limitations of this research is, it has used only secondary sources (medium resolution imageries) for selecting training data. These training data were used for supervised classification. Training sample references and references for accuracy assessment have been collected from secondary sources. In this research, stacked multiple seasons images have used to efficiently distinguish the land covers, as some land covers unlikely show same reflectance in all seasons. It required processing large amount of high resolution of images simultaneously. Google Earth Engine (GEE), which is a platform, enriched with a high-resolution data catalog with high performance computing functions (Gorelick et al., 2017) provides the opportunity to process a large amount of data from high resolution satellite imagery like Landsat and Sentinel (Oliphant et al. 2019). The platform more specifically provides internet-accessible application programming interface (API) and an associated web-based interactive development environment (IDE) for satellite image processing more efficiently. It also provides the opportunity of creation of prototyping and visualization of results swiftly (Gorelick et al., 2017). GEE also gives the privilege of processing big data from satellite images without downloading for cropland mapping, tree cover change detection due to natural disaster, disease etc., ecosystem mapping for both land and aquatic environment and so on (Shelestov et al., 2017). Shelestov et al. (2017) stacked three seasons images, where each season image is made into a median image of 6 to 12 images of that respective season. From each image we have selected 5 bands. So, the final stacked image was composed of all available images of that season. So, the input data of this research was heavier to manage. The major benefit of using GEE is that it let the researcher to process large volume of high-resolution imagery simultaneously on cloud without downloading (Oliphant et al. 2019). So, GEE has been used in this research for land cover classification.

2.3 Land Cover Classification:

2.3.1 Data:

2.3.1.1 GIS Shapefiles

Dhaka:

For this study, the city boundary shapefile for Dhaka has been collected and extracted from the digital database of "United Nations Office for the Coordination of Humanitarian Affairs" (https://data.humdata.org/dataset/administrative-boundaries-of-bangladesh-as-of-2015)website and from DDC (Development Design Consultant) based on the Draft Dhaka Structure plan Report (2016-2035) of the city development authority named 'RAJUK' of Dhaka city, Bangladesh

(RAJUK, 2015). The city boundary has been projected to World Geographic System 1984, a standard geographic projection system.

Kolkata:

The boundary shapefile for Kolkata Metropolitan Development Authority (KMDA) area has been collected from Stanford University online library (https://earthworks.stanford.edu/catalog/stanford-br919ym3359). Kolkata has different types of jurisdictional area like Kolkata Metropolitan City (KMC) and KMDA (https://earthworks.stanford.edu/catalog/stanford-br919ym3359/metadata). KMC contains only the core city area with CBD (Central Business District) where KMDA covers the suburban areas of Kolkata too. KMDA has been selected for better comparison with Dhaka Metropolitan Area (DMA).

2.3.1.2 Satellite Imagery

Landsat 7 Enhanced thematic mapper (ETM) and Landsat 8 Operational Land Imager (OLI) 30m time series images have been used for land cover classification. Images have been collected for last 15 years with a 5-year time span. Images were collected for years 2008, 2013, and 2018. The Landsat satellite series launched by the National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS) produce high quality imagery on a consistent basis. The blue, green, red, near infrared, short-wave infrared 1, and short-wave infrared 2 bands were used for the classification. Top of Atmosphere (TOA) images were used in lieu of Surface Reflectance (SR) images due to better availability. Temporal resolution of Landsat images is 16 days. For this analysis, median images of every images have been selected. The temporal median values of each band of each collection have been taken in this method and then computed to produce the resulted image (Gorelick et al., 2017). For identifying the difference between two seasonal composites, using 'median' images is instrumental (Gorelick et al., 2017).

Seasons have been selected in three temporal periods. Three dominant seasons are prevalent climatically in Bangladesh and West Bengal: (1) the dry winter season from December to February, (2) the pre-monsoon hot summer season from March to May, and (3) the rainy monsoon season which lasts from June to October (Shahid, 2011). Images have been collected according to those seasons. November 16 to February 15 as winter season, March 16 to May 15 as summer and June 16 to October 15 as monsoon have been selected as three seasons. All the images during a season have been taken to compute the median image of that season. To retrieve cloud free images, cloud masking algorithm has been used.

Table 2.1: Characteristics of multi-temporal Landsat 7 and Landsat 8 data (Oliphant, A. J., 2019)

Band Name	Landsat 8 OLI spectral range	Landsat 7 ETM+ spectral range
Blue	0.45-0.51	0.45-0.52
Green	0.53-0.59	0.52-0.60
Red	0.64-0.67	0.63-0.69
NIR	0.85-0.88	0.77-0.90
SWIR1	1.57-1.65	1.55-1.75
SWIR2	2.11-2.29	2.09-2.35

2.3.2 Methodology:

2.3.2.1 Classification and Training sample

There are two types of classification, which are supervised and unsupervised (Doski, 2013). Supervised classification is where a user can select sample pixels from an image representing a specific class and the image processing software has been used those to classify the image. Training sites are selected based on the knowledge of the user. Software processes the image using maximum likelihood, and minimum distance based on statistical analysis (Doski, 2013). Whereas, unsupervised classification is where the user has no prior ground information. The computer decides which classes are related and shows them to the user. The user must define the classes and number of classes. Using specific statistical criteria, the pixels having same or close spectral characteristics are grouped in the same class (Wang and Cheng, 2010).

In this study, the supervised classification method has been applied using GEE. Google Earth Engine uses satellite images from NASA as well as the Landsat Program and provides the opportunity to do land cover classification and other spatial analysis online (Patel et al., 2015).

There are numbers of supervised classification methods. These are Bayes, Classification and Regression Trees (CART), Random Forest, Support Vector Machine (SVM), Perceptron, Mahalanobis, etc (Patel et al., 2015). CART method has been used in this research

CART was introduced by Breiman et al. (1984). It is a powerful tool for land cover classification based on large tree method (Pham, B. T., Prakash, I and Bui, D. T., 2018). The two approaches in this method are classification tree and regression tree. Classification tree works on predefined class and regression tree does not work on predefined class. Regression tree predict classes and classification tree classify based on new observations (Choubin et al., 2018).

In this study, the images have been classified in six classes. These are Waterbody, Vegetation, Built-up, Barren land, Wetland, and Agriculture. For classifying these selected classes, training samples have been collected using secondary data and google earth view. Historical images of selected time periods of Dhaka city and Kolkata were used as the reference of selecting training sample data. For 2018-19 image, google earth time series maps and google map have been selected as a reference. Local knowledge of authors has also been used as a reference for selecting training samples. Both true color images and false color images have been used for better understanding during selection of training sample data.

Wetlands in cities have lower depth and are mainly visible during the rainy season. Waterbodies have higher depth and exist all the year round. Agricultural lands look green during the cropping season, but low-lying agricultural lands are flooded during the rainy season. As a result, during the rainy season wetlands, waterbodies, and agricultural lands merged with one another in many areas and become hard to identify. Image stacking made it possible to identify wetland, waterbody, vegetation, and agricultural lands separately and properly. In GEE, it is possible to train the classification function with the training sample from multiple images. Training samples for waterbodies were selected from images of winter and summer season's images. The differences of waterbodies from the rainy season and the winter season were selected as training sites for wetlands.

Training samples for agricultural lands were selected from winter and summer season's images considering winter (Rabi) crops season, which lies between November and April in Bangladesh (Mohsenipour et al. 2017). During the cropping season, difference between vegetation and agricultural land lie in their irregular and regular shapes respectively. So, the training samples for these four classes have been selected accordingly. Selection of training samples for barren land is quite challenging. Some agricultural lands can look like barren land after cutting off crops. There is possibility of merging of wetland and barren lands too. Therefore, training sites for barren land were selected from the rainy season images, considering those barren lands which are not too low to be submerged by flood waters. Training sites for built-up areas were selected from all season's images, as it is not mutually exclusive from other land covers.

Number of training samples were selected considering the quality of the imagery and convenient understanding of classes over the years, and seasons as well. The difference between waterbody, wetland, agricultural, and barren land largely depend on the difference of monsoon image with other images. Often cloud free and clear images were not available during monsoon periods. Therefore, there may still be some errors in classification for that reason.

Before executing classification, three seasons images have been merged using the 'addBands' function which added the bands of all three images. Then the training samples have selected from each three images based on the requirement of distinguishing land cover types. The classification was executed on the merged image which had all the bands of the three seasons images. Classification function was trained by giving training samples of respective classes from that seasons image/images which represent that class most efficiently. The classification function classified the classes based on different pixel values of respective classes from any season.

In this research, CART models make a class prediction for each pixel using the predictor variables of regression tree that were used as inputs to that CART model. It took the observations from the user and made classes of dependent variable using some exogenous rules using the classification tree.

2.3.2.2 Image processing using Google Earth Engine (GEE)

This study used (CART) method in GEE. This study stacked multi-seasons images which makes it possible to distinguish some overlapped land covers. Merging high resolution imageries was possible for using GEE because it uses the images from cloud and process also in clouds. In this study, 24 images for each year have been merged and processed simultaneously where five bands were considered for every single image. Besides, three merged images from three years were in function simultaneously for distinguishing the classes. As a result, the system has processed a large data containing 72 images and their bands. Processing these large datasets in a single computer system require high configuration and speed. As a result, this study has used cloud-based GEE to execute the analysis. This study also validated the classification results using accuracy assessment method (Accuracy assessment results are explained in the analysis part). Though the accuracy was below 80%, this study paved the way to employ online satellite image processing using cloud data for this region.

2.3.2.3 Accuracy assessment

This study took all the images of the selected years. In monsoon period, most often Landsat images have significant amount of cloud cover. As a result, selecting pixels from the images of monsoon periods created some null values. To minimize errors, this study took pixel values from monsoon images only for wetland areas. Accuracy assessment of the classification have been done by "Error matrix (confusion matrix) method". Error matrix algorithm compares ground truth data taken as the true reference point of specific land covers with results of classification. The study also measured kappa coefficient which is a parameter to assess how much better the classification is than a random classification. The study then measured the user's accuracy which is the proportion of the pixels of a specific class which have been correctly classified on the total pixel assigned to that particular class. The study also measured producer's accuracy which is the number of correctly classified pixels of a class / number of reference pixels. Accuracy assessment results for Dhaka and Kolkata have explained in the analysis section.

2.3.3 Limitations in Base Map Preparation and Accuracy Assessment

There are few limitations in land cover classification and accuracy assessment. There are some specific reasons for that.

1. This research has used all the satellite images of the selected years for land cover classification. In monsoon period, almost all the Landsat images have cloud covers. Wetlands training samples were taken from monsoon images where there were cloud covers. So, taking training samples from these images created some error in classification.
2. There were few incidents where the spectral signature of barren land and built up area were close. Landsat has 30m spatial resolution. Usually, agricultural lands are smaller, and it

was hard to agricultural land and vegetation. QUICKBIRD, IKONOS or other high-resolution images could minimize the errors in classification.

3. Another limitation is the reference data. it is important for ground truthing purpose. Google Earth time series images were taken as reference. Some literatures images were also have taken as reference data, but extensive field survey could minimize the errors in classification.

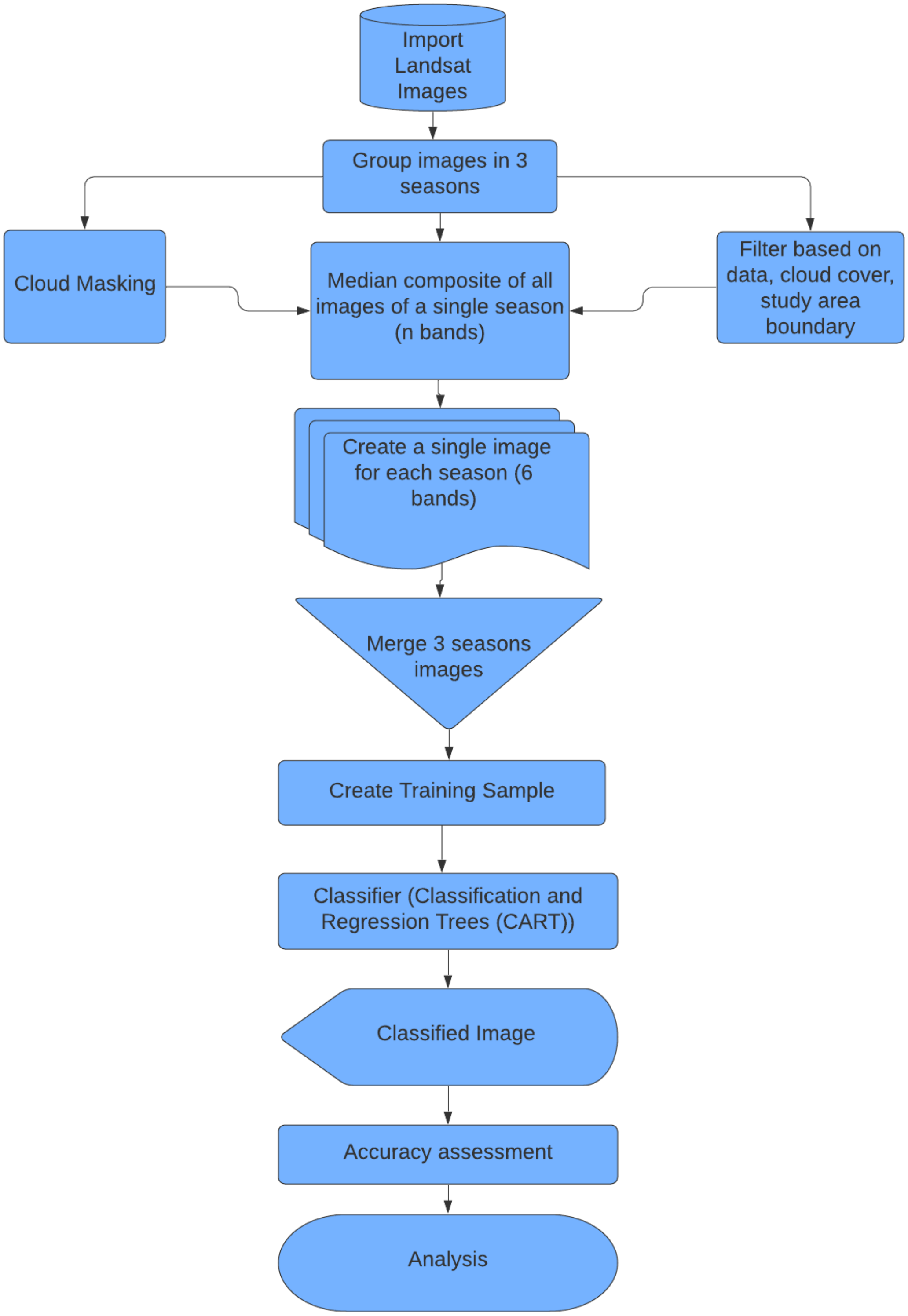


Figure 2.8: Flow Chart of Land Cover Classification in GEE

2.4 Land Cover Classification of Dhaka

For Dhaka, training samples have been taken for better understanding and accuracy. As most monsoon images have clouds, more samples have been taken for wetland from the monsoon images. As vegetation merges with agricultural lands often, more samples have been taken for vegetation to distinguish it from agricultural land.

Table 2.2: Training samples of the study area

Class Name	Year-2007-08	Year-2012-13	Year-2017-18
Waterbody	31	36	22
Vegetation	55	83	53
Built Up	51	36	29
Barren Land	43	29	49
Wetland	23	21	42
Agricultural	21	29	29

2.4.1 Results and Discussion:

The city of Dhaka has been established on south-western part of the bank of the Buriganga River, and the river had also a profound impact on its development and growth. The city has established on eastern bank of the river.

2.4.1.1 Geographical Change

Figure 2.9 shows the land cover of Dhaka in 2008, 2013 and 2018. It shows that the urban built up area was concentrated in the southern part, more specifically along the bank of Buriganga in 2008. The northern part was mostly barren land and vegetation and waterbody were on the eastern part of the city. In 2013 urban built up area increased. It has spread through the northern part of the city from 2008 to 2013 and majorly from 2013 to 2018. From the expansion pattern, it seems that there was a lot of dependence on the Buriganga River but with time and urban growth that dependency diminished.

Principally the barren land has been transformed into urban built up area. Waterbodies in the north-eastern and western part has been transformed into greenspace. There were still some waterbodies in the center and north-western part of the city. In 2018, the urban built up area expanded in south-eastern part and in the center of the city. A large green area in the eastern part has been transformed into barren land. Waterbodies in the center of the city have also been narrowed and changed into barren land and impervious surfaces. Overall, the eastern part of the city has experienced major change in these time periods than other parts of the city. The change detection map can explain the overall change of the city from 2008 to 2018 (Appendix).

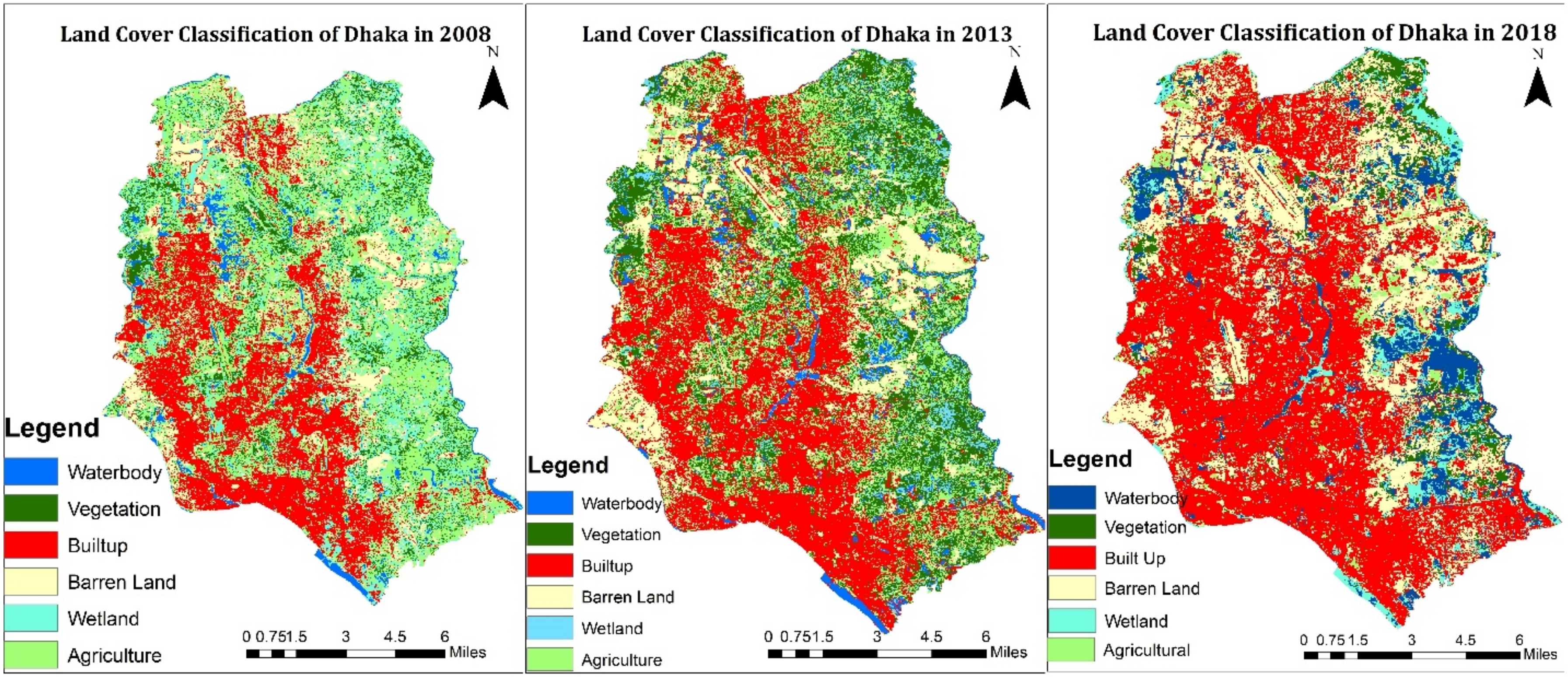


Figure 2.9: Land Cover Changes of Dhaka in 2008, 2013 and 2018.

2.4.1.2 Statistical Change

Statistically land cover change of Dhaka gives some interesting facts. The change of waterbody is consistent and has no surprising ups and downs. From 2008 and 2018, about 30%of the waterbodies have decreased (Table 2). Agricultural lands Agricultural lands have also decreased significantly from 2008 to 2013. It has increased in small amount in last 5 years. The city has experienced consistent increase (188%) of built-up areas from 2008 to 2018. Amount of barren land has also decreased at a notable amount from 2008 to 2013 and surprisingly it has increased again in next 5 years. Wetlands have increased in noteworthy manner. Vegetation have showed different scenarios in these two periods. From 2008 to 2013, vegetation has increased by 38% of its total amount but it lost of its 83% landcovers in next 5 years.

Table 2.3: Statistical table of Land Cover of Dhaka from 2008 to 2018

Land Cover Type	Land Cover Area (In percentage)			
	Land Cover in 2008	Land Cover in 2013	Land Cover in 2018	Changes from 2008 to 2018
Waterbody	3.64	3.75	8.71	5.07
Vegetation	10.31	21.14	6.23	-4.08
Built Up	25.99	34.03	51.21	25.22
Barren Land	15.97	15.19	26.64	10.67
Wetland	14.68	6.00	7.21	-7.47
Agriculture	29.41	19.88	3.57	-25.84

The visual and statistical analysis of temporal land cover change over these periods reveals one fact that, in Dhaka generally the process of increasing built-up area has few steps.

Except vegetation and barren lands, all other land covers consistently increased or decreased. Figure 2.9 shows that these two land covers changed among themselves in a large extent. Vegetations have increased from 2008 to 2013 but have decreased from 2013 to 2018 surprisingly. Moreover, barren land has been decreased rapidly from 2008 to 2013 but increased at a significant amount from 2013 to 2018.

The visual analysis of the image's states that, in the first step, waterbodies and agricultural lands convert into vegetation or wetlands, then the vegetation or wetlands transforms into barren land and in the next step it converts into impervious land surfaces. It also states that, transformation of barren lands always results into built-up areas. Again, the waterbody which transformed into vegetation may not be the real vegetation rather it may be the dumped waterbody/wetlands which has water hyacinth and other aquatic plants which seems like vegetation from the satellite.

Without image-stacking in GEE, these wetlands and agricultural lands could be identified as waterbody and vegetation. Image stacking and the provision of taking training samples for each land covers from their best representative season's images respectively made it possible to delineate every land cover exclusively.

The figure 2.9 further shows that, in 2008, in the north-east and north-west part of the city, there were many wetlands and agricultural lands. Mainly these wetlands and agricultural lands have converted into barren land from 2008 to 2013. Some of these barren lands have transformed into barren land in the next 5 years. Increasing of wetlands may happen due to increasing of flooded area during monsoon as the city is losing its flood flow zones (Rahman, M.A. and Islam, S., 2019). It may also be the fact that, the waterbodies have been dumped with soil and it remains fallow for some time before the establishment starts. Another reason can be people's tendency to fill up waterbody and use it for growing crops for more profit till they utilize the land for more remunerative purposes like urban establishments. In the period before establishment, grass grows there, and the area seems like perfect vegetation in the land covers.

2.4.1.3 Accuracy assessment of Dhaka

The classification system used google earth historical imagery from "Google Earth Pro" software as reference for the land covers. The study also has used historical imageries of Dhaka from RAJUK and other organizations. Literatures on land cover classification of Dhaka and historical urban growth of Dhaka was also used for the zonal reference of specific land covers in a region of the study area. Accuracy assessment has been done using error matrix (confusion matrix) method which takes all the training sample data and validate the classification result. About 50 random points have been selected as reference point based on ground truth data for accuracy assessment. According to Table 2.4, the accuracy results also show that, the classification was efficient.

Table 2.4: Results for Accuracy Assessment of Classified Output (Conditional Kappa (K^) Statistics)

Category	Years		
	2008	2013	2018
Overall accuracy	95%	94%	95%
Kappa value	0.95	0.93	0.94
Producers accuracy	93%	91%	95%
Users Accuracy	95%	96%	91%

Land covers of Dhaka have been changing since its declaration as a capital city right after the nation of Bangladesh was born in 1971. The city, which has massive demand on land resulting from increasing population, experienced change of land covers gradually over the last few decades. At the same time, few landcovers changes temporarily over the years such as waterbody to wetland, wetland to vegetation, vegetation to barren land and agricultural to barren land with the change of seasons. Though these conversions are temporary, these conversions work as a step to the ultimate conversion of any land cover to build up area. Land cover change detection using multi seasonal images makes it convenient to distinguish the land covers which have close range pixels and overlap with one another throughout the year. Delineating these land covers also explained unique patterns of land cover change from visual analysis. The pattern reveals how the land covers of the city has been changing so far gradually, and more strategically. This strategic land cover change is responsible for the loss of waterbody, vegetation, and other natural landscapes of the city. Most often, these land covers changes seem natural and draw no attention to the policy makers or conservationist of natural landscapes. This multi-seasonal image analysis using GEE can identify these alteration works as the foundation of dynamic land cover policy.

2.5 Land Cover Classification of Kolkata

The city of Kolkata is becoming a megalopolis from metropolis in a very short time. In last 100 years, the city population has been increased by 100 times (Mandal et al. 2019). The city has experienced significant human induced land cover change, followed by adverse impacts of air, sound and odor pollution and deterioration of the city's civic life. In last 30 years, built have been increased from 23% to 57% of the total land covers of the city. Vegetation has been dropped from 35% to 19% over the period. Most surprisingly, half of the fallow lands of the city has been transformed into other types of land covers in this time. If the trend goes, then close to 70% of the city will become impervious areas making it more susceptible to urban heat island and other urban issues. The natural landscapes will be confined within 20% area of the city (Mandal et al. 2019).

2.5.1 Results and Discussion

2.5.1.1 Geographical Change

Figure 2.10 shows land covers of Kolkata in 2002, 2013 and 2018. Kolkata city was established on both sides of the river Hooghly. KMA contains areas on both sides of the river. On eastern bank of the river, urban growth and development was more significant from early stage of the city. Hooghly river shares the major portion of the waterbodies of the city. except river Hooghly, there are few waterbodies on the eastern fringes of the city. Figure 2.9 shows that, waterbodies of the city increased from 2008 to 2013 but then decreased again in 2018. Transformation of the waterbody in the southern side of the city to wetland and agricultural land is the reason for decreasing the share of waterbody in KMA's landcover.

The figure also shows that wetlands of KMA has decreased dramatically from 2008 to 2018. The northern side and southern side had few wetlands in 2008 which have been disappeared mostly by 2018.

Vegetation has been decreased at a significant rate from 2008 to 2013. From 2013, the rate has been slowed down. Primarily, northern and southern part of KMA had high concentration of vegetation in 2008. Vegetation in southern and south-western side have been decreased over the time period. In other areas, concentration of vegetation has been decreased almost equally. Figure 2.9 shows that, from 2013 to 2018, the distribution of vegetation was almost equal.

Agricultural lands are significant in eastern and southern part of KMA. In eastern part of the city, agricultural lands exist close to the waterbodies. The urgency of water supply for agriculture can explain the distribution pattern of agricultural lands. Agricultural lands are also clustered in some places. There is no significant change of agricultural lands distribution over these years from visual interpretation.

KMA has experienced noteworthy change of built-up areas over the selected years. The increase of built up areas was remarkable during second slot of the selected time period (2012 – 2013). Concentration of built up areas is higher at the center of the city on both side of the river Hooghly. Three bridges named Vidhyasagar setu, Howrah bridge and Vivekanda setu made a connection between the two sides of Hooghly river. That can be one of the reasons behind concentration of built up areas on both side of the river, which was not the case for Dhala city across the Buriganga river. Comprehensively, the central part and the peripheries of the central part of the city has experienced major changes within the selected ten years time periods. It reveals that the development pressure is on the central areas and areas surrounding it in Kolkata. The change detection map explains also this situation (Appendix)

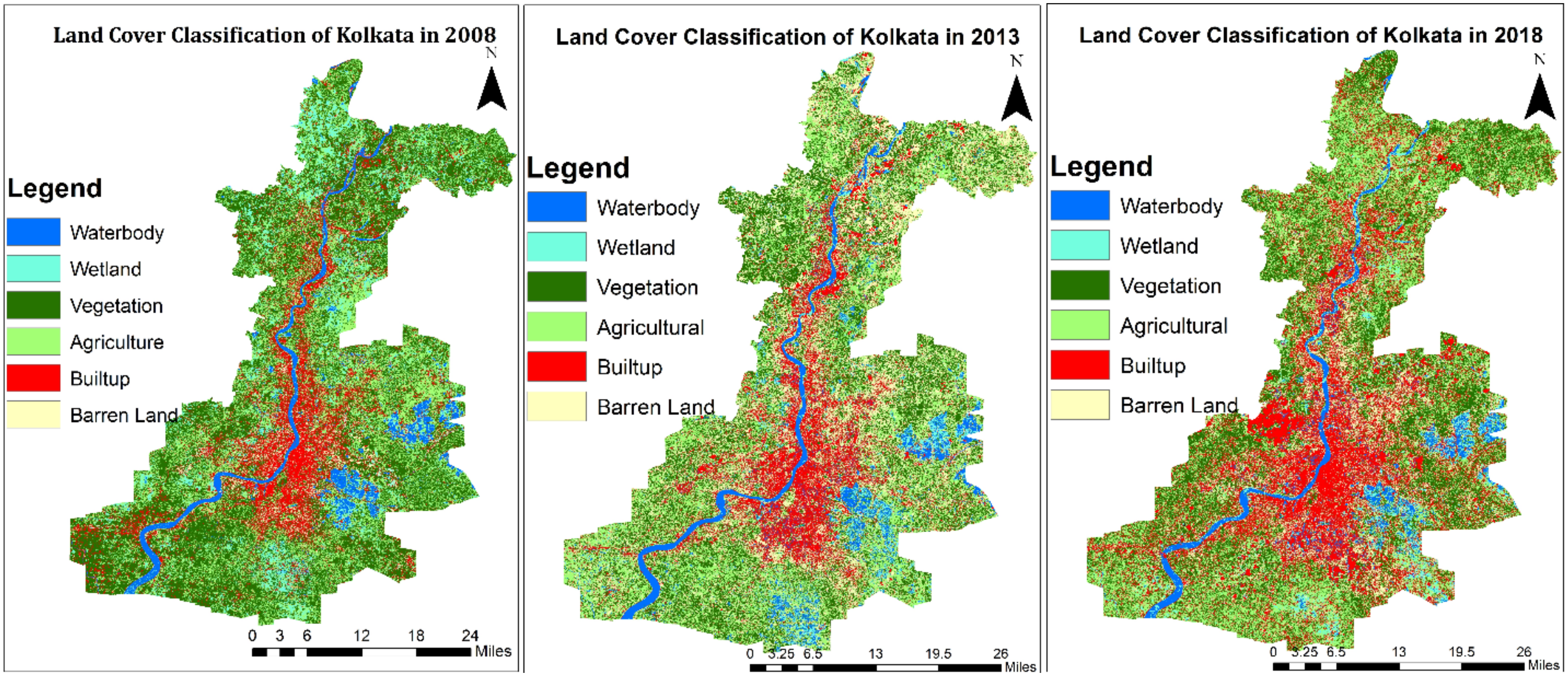


Figure 2.10: Land Cover Changes of Kolkata in 2008, 2013 and 2018

Figure 2.10 shows that, the portion of barren land in 2008 was more significant than other two time periods. In 2008, barren land existed on the northern part of the city. there were also some barren lands at the center of the city. In 2018, barren lands at the center of the city remained but on the northern part of the city transformed to other types of land covers.

2.5.1.2 Statistical Change

Table 2.5: Statistical table of Land Cover of Kolkata from 2008 to 2018

Land Cover Type	Land Cover Area (In percentage)			
	Land Cover in 2008	Land Cover in 2013	Land Cover in 2018	Changes from 2008 to 2018
Waterbody	5.10	7.45	5.25	0.16
Wetland	9.50	2.21	3.13	-6.37
Vegetation	42.22	27.02	26.95	-15.26
Agriculture	26.13	26.01	27.69	1.56
Built up	14.47	14.69	26.32	11.85
Barren land	2.54	22.56	10.61	8.07

Table 2.5 shows the percentage distribution of landcovers of Kolkata in three time periods. Table shows that, percentage of waterbody is always insignificant in Kolkata (5 – 7 %) . The share rises from 2008 to 2013 but it decreases again in 2018. Except the Hooghly river, there are very few waterbodies in Kolkata at the eastern fringe areas of KMA.

Portion of wetlands also have decreased in these time periods at a faster rate. In 2008, KMA had about 10% area as wetlands which becomes less than 4% in 2018. Vegetation is the landcover which experienced highest extinction. Almost 40% of all the vegetations have disappeared within 15 years. Agricultural haven't changed much but showed consistency and is concentrated outside the main city boundary. Agricultural lands exist in eastern and western part of KMA. Built up areas have increased by 100% in these time period. Barren land showed some interesting statistics. It has been increased by 11 times from 2008 to 2013 but again 50% of the barren land again disappeared by 2018. Sharma et. Al (2015) worked on KMC and found less than 5% area as wetland vegetation in 2010. KMC contains mainly the CBD of Kolkata and as the agricultural land are mainly outside the CBD, it showed a different scenario for KMC. The scenario of sparse settlement (mainly barren land) and dense settlement (mainly built-up) shows the trend of barren land and built up lands in KMA too.

Sahana et. al. (2018) worked on KMA and found that the change of agricultural area (combinedly agricultural land and agricultural fallow land) had minimal changes from 2000 to 2015. He also found similar kinds of changes of land covers for Kolkata in those time periods. In the study period, non-urban area has decreased due to rapid urbanization of KMA.

Figure 2.10 shows that, though both banks of Hooghly river has built up and barren land, concentration of urbanization is dominant on the right bank (eastern part of KMA) of the river. One of the reasons can be the existence of KMC on the right bank. Jahan et. al. (2015) and Mukherjee (2012) also found that, municipalities on the suburban areas had more urbanization rate from 2000 to 2015. The figures also show that expansion of built up and barren lands are occurring along the river.

2.5.1.3 Accuracy Assessment of Kolkata

Table 2.6: Results for Accuracy Assessment of Classified Output (Conditional Kappa (K^) Statistics)

Category	Years		
	2008	2013	2018
Overall accuracy	94.7%	93%	94%
Kappa value	0.93	0.92	0.92
Producers accuracy	93%	91%	92%
Users Accuracy	94%	93%	95%

About 50 points have been selected as reference point based on ground truth data for accuracy assessment. The reference points have been selected randomly. Then the confusion matrix and error matrix function were used in GEE for the accuracy measurement. Table 6 shows that, for Kolkata overall accuracy ranges from 93 to 94%. Producers and user's accuracy ranges from 91% to 95%.

Comparison between Dhaka and Kolkata:

Dhaka is an older city than Kolkata. Partition of Bengal, Indian independence and independence of Bangladesh, all of those political events have boosted up the urban growth and expansion of built-up areas. The land cover of Dhaka has been changed with the change of urban areas simultaneously. Temporal changes of land cover in three time periods reveals that, there may have a pattern of land cover change in Dhaka. Though the end result of most land covers is to transform into built-up area, there are few stages. Most often, very unlikely waterbody or vegetation directly transform into built-up areas. There are some laws regarding transformation of flood flow zones, waterbody and vegetation in Dhaka structure plan. According to the land cover change, waterbody and vegetations are transformed into wetland or agricultural land. In the second step, wetlands and agricultural lands are filled and prepared for development. In this stage, land covers become barren lands and then those barren lands transform into built-up areas.

Kolkata is comparatively a newer city of south Asia comparing its significance. All of the political events have an impact on Kolkata's urban development. Kolkata is divided into two parts by the river Hooghly. Initially, the development started on eastern side of the river but after a passage of time, both side of the river has been developed. The connectivity of two side of river Hooghly can be one of the reasons behind that. Though, Kolkata has been developed on both side, central part of the city has more significance. Establishment of urban areas has been largely influenced by the river as urban built-up concentration is mostly aligned on the bank of the river. Land cover change of Kolkata over three time periods reveals that, Kolkata's agricultural land has been consistent over these years. Built-up areas and barren lands have increased. Hooghly river is the main part of waterbody for Kolkata, so transformations of waterbody didn't happen there. Kolkata lost its vegetation and wetlands in these time periods but still the urban concentration is clustered in the central part of the metropolitan area.

CHAPTER 3: IMPACT OF LAND COVER CHANGE: AIR POLLUTION

3.1 Land Cover Change and Air Pollution: Global Perspective

Land cover change is a global common phenomenon. It is more prevalent in South Asian countries where land per capita is below 5 sq. km. per 1000 people (Nationmaster, 2008). Due to high demand on land, cities of south Asia have experienced dramatic land cover changes followed by massive urbanization. Coincidently, several cities in South Asia have become some world largest mega cities. Some of these megacities also marked their footsteps in the list of most polluted cities (Marlow and Dormido, 24 Feb. 2020). Land cover change has some impacts (Loarie et al. 2011). Some visible direct impacts are unplanned urbanization, deforestation, agricultural loss, urban heat island (UHI) effect, and variation in biogeochemical processes (Deng et. Al. 2013). Among these impacts, land covers impacts on biogeochemical process is the least prioritized topic of research specially in south Asian cities. Impacts on biogeochemical processes are several types. Among them, the impact on pollution caused by the absorption of greenhouse gases and creation of particulate matter (PM) in large concentrations (Deng et al. 2013).

Among all the pollutants on earth, particulate matter is regarded as the most important especially for health effects and reduced urban visibility (Begum et. al. 2008). Urbanization rate, more specifically increasing rate of urban built up areas and other impervious surfaces followed by increasing number of roads, vehicles, industries etc. is one of the main reasons for the creation of particulate matter. Han et. al. (2014) discussed the significant impact of urbanization on particulate matter concentration. They found significant positive and strong correlation between urban PM2.5 concentration and urban population (0.99), urban PM2.5 concentration and urban secondary industry fraction (0.71), and urban PM2.5 concentration and urban built up area size (0.36) (Han et. al. 2014). Lo and Quattrochi discussed how urban-induced convergence zone in the southern cities of the United States has become the areas of high ground-based ozone concentration. They also found that, rapid highway development, urban sprawl and peri-urban fringe areas have higher concentration of ozone. Feizazadeh and Blaschke (2013) also found that higher pollution concentration is attributed to the commercial and highly populated areas generating large amount of traffic. Air pollution in South Asian cities are correlated with industrialization, urbanization and increased demand from the energy sector (Vadrevu et. al. 2017). Ostro et. al. (2011) identified secondary sulfate/organics (power plants, ship emissions, long-range transport), road dust (brake/tire/road wear and restrained PM), minerals (urban and construction dust), fuel oil combustion (ship emissions and industrial combustion), industrial (process emissions), secondary nitrate/organics (mobile sources and other fuel combustion), vehicle exhaust, and aged sea salt as the sources of PM2.5 and PM10 in Barcelona, Spain.

Begum et. al. (2008) found that diesel-powered vehicles, two stroke engine gasoline vehicles, and brick kilns are the major sources of particulate matter for Dhaka. These findings attribute to urbanization, increasing urban built up, decreasing of natural landscapes to atmospheric pollution increase, more specifically particulate matter concentration of cities.

3.2 Air Pollution in South Asian Cities: Dhaka And Kolkata

Urban areas across the world occupy almost half of its population where urban centers and megacities are thought to be the major sources of air pollution (Akimoto, 2003). World Health Organization (WHO) says that most of the people around the world must breathe polluted air (Mendoza, 2018). Particulate matter is one of the major pollutants which is composed of solid and liquid particles, varied and in size and suspended in the air (Gupta et al., 2006). It is also responsible for lung cancer and other respiratory diseases. The cross-sectional study considering land cover, air pollution and asthma hospitalization by Aclock et. al. (2017) discovered that number of hospitalizations can be reduced by increasing urban natural environments. In Asian countries, air pollution is also increasing at a rapid rate with the increasing economy. In Indian subcontinent, land use is one of the major factors for air pollution (Leliveld et al., 2001).

Dhaka is one of the fastest growing megacities in the world. Currently the city has 8.9 million people in an area of 590 sq. miles. Large population along with a lot of infrastructures, transports and impervious surfaces are contributing to the air pollution of the city (Dhaka Structure Plan 2016—2035, 2015). In 1996-97 air pollution of the city was severest and concentration of lead was the highest than any other place in the world. From 2002 to 2010 PM2.5 has increased from 69.11 μg/m3 to 83.91 μg/m3 where the standard for the country was 15 μg/m3 (Motalib and lasco, 2013). Other pollutants have also increased by the passage of time. Moreover, a lot of new massive construction works like metro rail, flyover, widening the streets, establishment of UBER resulting to increasing the number of private vehicles on the road, new residential areas started in this decade has accelerated the pollution in the city. (Begum et al. 2013).

The ambient air quality of Kolkata is deteriorating day by day too. Being the capital of West Bengal state and one of the largest megacities in India, it has significant population pressure. Many people from the nearby suburbs also come to the city every day for job and other activities. Suspended particulate matter concentration in the city varies from 227.1 μg/m3 to 397 μg/m3 with an overall mean concentration of 310 μg/m3 (Ghose, Paul and Banerjee, 2004). It is far worse than the National Ambient Air Quality Standard (NAQS) (Ghose, Paul and Banerjee, 2004).

This chapter derives air pollution map (Particulate Matter 2.5 for Dhaka and Particulate Matter 10 for Kolkata) from Landsat satellite images and ground station data. It also discovers how is air pollution and land uses are correlated for the two cities, Dhaka and Kolkata.

3.3 Air Pollution Mapping Methods

Satellite remote sensing for pollution mapping is becoming a new and exciting way to measure the pollution of a space specially the aerosol. Instruments were sent from the satellite to measure pollution like Carbon Monoxide (CO) in 1981 through Columbia satellite. Pollution mapping from satellite in south Asian cities has become popular in very recent times (Akimoto, H., 2003). Traditionally, air pollution is measured by using ground-based stations which incur large costs for installation and maintenance. In Dhaka, there are only 3 clustered stations (DOE, 2019) giving monthly pollution data from 2012 inconsistently. In Kolkata, 16 stations have been collecting 4 types of pollution data from 2002 on an inconsistent daily basis (WBPCB, 2019). For the developing world's cities especially in south Asia, it is hard to maintain ground-based stations. So, pollution measurement through satellite data is easier and efficient here.

Satellite systems like TERRA and AQUA have made pollution mapping from satellite image easier. Terra was launched at 18th December 1999. NOAA is another US satellite collects climate, clouds and air quality data which are freely available. The additional benefits of TERRA are that it has a special sensor for collecting clouds, air quality and pollution data named moderate resolution imaging Spectro-radiometer (MODIS) from its orbiting satellite. AQUA started to collect data from 2002 (Sohrabinia and Khorshiddoust, 2007). The difference between TERRA and AQUA is only the time of collecting data over a day. Some studies also used ETM+ sensor of Landsat 7 and OLI sensor of Landsat 8 to retrieve pollution map of PM10 (Mendoza. C.I.A. et al., 2018). In those study aerosol optical thickness (AOT) has been used to measure the pollution. AOT is the atmospheric extinction from the ground surface to the top of atmosphere. There are some challenges to do this. One is satellite derived quantities provide columnar information for conditions whereas particulate matter represents near-surface dry mass concentrations. Other issues are variations of aerosol and hygroscopicity (Gupta et al., 2006).

Aerosols in the atmosphere are found in three size ranges: (a) very fine transitional smaller than 0.1 m. (b) fine particles in accumulation mode between 0.1 to a few micrometers and (c) coarse particles more than a few micrometers (Sohrabinia, and Khorshiddoust, 2007). Objects smaller than the wavelength of satellite sensors cannot be detected, so only the last group of aerosols can be detected by MODIS bands. Band combinations of 1, 3 and 7 of MODIS image can be used to extract this map. Bands 1 and 3 cover optical region of electromagnetic spectrum, so it can be used to collect information on aerosols and particulate matters while band 7 covers infra-red region (2105–2155 nm) and can be used for calibration purposes only (Sohrabinia, and Khorshiddoust, 2007).

Landsat images also provides data of the distribution of aerosol optical thickness (Sifakis, 1998).

3.4 Method

This study tries to find the impact of land cover changes of Dhaka and Kolkata on the concentration of particulate matter. In this study, pollution maps are made both for Dhaka and Kolkata in years 2014 and 2018. Land cover changes were from years 2008 to 2018. Particulate matter pollution mapping have been done from 2014 and 2018 because of data availability. Pollution mapping done at the same time periods of land cover change can explain the correlation between changes of landcover followed by changes of pollution both temporally and spatially. Following methods ere used for this study.

3.4.1 Data Acquisition

In this study, Landsat satellite images of 2014 and 2018 were used for producing air pollution map. Landsat 8 Operational Land Imager (OLI) and TIRS sensor was used in this study. Spatial resolution of Landsat is 30 m which is better than other freely available satellites like MODIS and gives more accurate results (Fernández-Pacheco et. al. 2018). Table 3.1 gives the information of the Landsat data used in this study and their spectral and spatial resolution.

Table 3.1: Landsat Data used for Pollution mapping

Band Name	Landsat 8 OLI spectral range	Spatial Resolution
Blue	0.45-0.51	30 m
Green	0.53-0.59	30 m
Red	0.64-0.67	30 m
NIR	0.85-0.88	30 m

For NDVI, NDBI and NDWI calculations same Landsat images were used. Table 3.2 represents the Landsat data acquired for two study areas for 2014 and 2018.

Table 3.2: Landsat data of Study location

	Landsat Data for the Study			
	Dhaka 2014	Dhaka 2018	Kolkata 2014	Kolkata 2018
Date	30-MAR-14	21-FEB-18	05-MAR-14	28-FEB-18
Path	137	137	138	138
Row	44	44	44	44

Ground station data were collected from different sources. PM with particle size less than 2.5 microns (PM 2.5) data were collected for Dhaka and Particulate Matter with particle size less than 10 microns (PM 10) data were collected for Kolkata.

For Dhaka, ground station data were collected from 3 different sources.

1. Monthly report of Clean Air and Sustainable Environment (CASE) project (CASE, 2019).

2. Dhaka US Consulate Air Pollution: Real-time Air Quality Index (AQI) (World Air Quality Index, 2020).
3. Berkley Earth's daily Regional Average Particulate Air Pollution (PM2.5) Dhaka, Bangladesh (Berkeley Earth, 2020).

In 2014, six ground station data were used. In 2018, 10 ground station data were used.

Table 3.3 and 3.4 shows the ground stations and pollution data associated of study areas in Dhaka (maps attached in appendix). Ground stations were insignificant in the exact study area. So, ground stations in the area of the satellite images were also taken for analysis. Pollution map have made for the whole area of the satellite image and then clipped to the study area.

Table 3.3: Location of Ground station and Pollution in 2014

Place	Longitude	Latitude	PM 2.5 (µg/m3)
Farmgate	90.39	23.76	75.2
Darus Salam	90.36	23.78	91.2
Gazipur	90.42	23.99	99.1
N.Ganj	90.51	23.63	86
Gazipur	90.42	23.99	113
Notun Bazar	90.43	23.8	115

Table 3.4: Location of Ground station and Pollution in 2018

Place	Longitude	Latitude	PM 2.5 (µg/m3)
Farmgate	90.39	23.76	167
Darus Salam	90.36	23.78	171
Gazipur	90.42	23.99	174
N.Ganj	90.51	23.63	165
Us Consulate	90.43	23.8	166.5
Dhaka	90.41	23.71	156.7
Kishoreganj	90.78	24.44	166.5
N.ganj	90.5	23.61	138.6
Paltan	90.41	23.74	137.1

Tongi	90.4	23.89	142.1

For Kolkata, ground station data were collected from

1. Open Government Data (OGD) Platform India (OGD, 2020). And
2. Air Quality Information System of West Bengal Pollution Control Board (WBPCB) (WBPC, 2020).

Table 3.5 and 3.6 shows the ground stations and pollution data associated in the study area of Kolkata (map attached in appendix). For Kolkata, all ground stations were within Kolkata as WBPCB collects data from a good range of ground stations. There is still some inconsistency of collecting the data. Data collected from one station in 2014 had unavailability of data in 2018 in some cases. In that case, closer ground stations data were used as proxy data.

Table 3.5: Location of Ground station and Pollution in 2014

Place	Longitude	Latitude	PM 10 (µg/m3)
Dunlop Bridge, Kolkata	88.38	22.65	153
Baishnabghata,Kolkata	88.38	22.47	45
Behala Chowrasta,Kolkata	88.31	22.49	92
Salt Lake, Kolkata	88.42	22.59	123
Minto Park, Kolkata	88.36	22.54	140
Cossipore Police Station, B.T. Road, Kolkata	88.38	22.62	206
Lal-Bazar, Dalhousie Square, Lal Bazzar Police Headquarter, Kolkata	88.35	22.57	207
Paribesh Bhawan	88.41	22.56	101.5
Shyambajar	88.37	22.6	154.33
Ultadanga	88.39	22.6	145.33

Table 3.6: Location of Ground station and Pollution in 2018

Place	Longitude	Latitude	PM 10 (µg/m3)
Dunlop Bridge, Kolkata	88.38	22.65	161.33
Baishnabghata,Kolkata	88.38	22.47	98.33
Behala Chowrasta,Kolkata	88.31	22.49	121.67
Salt Lake, Kolkata	88.42	22.59	97.33
Minto Park, Kolkata	88.36	22.54	119.33
CESE, Mandevitle Garden (Gariahat)	88.37	22.52	129.33
Paribesh Bhawan	88.41	22.56	124.33
Shyambajar	88.37	22.6	131.33
Ultadanga	88.39	22.6	144.67
Beliaghata	88.39	22.57	97
Tollugunge	88.35	22.5	92
Topsia	88.4	22.54	132.33

3.4.1 Data Processing

Backscattering to space by particles and molecules creates atmospheric path radiance

in the atmosphere (Techarat, 2014). Spectral radiance of the surface recorded by a satellite received at sensor, represent the modified spectral radiance of the surface. This radiance is absorbed by Aerosol and Particulate Matter. To obtain the true radiance, the recorded values need to be corrected using the sensor calibration can correct the radiance by using TOA reflectance and sensor radiance. During pre-processing of some remote sensing data, path radiance is removed from the image which mainly contain the noises created by aerosol. In this study, “atmospheric path radiance” is calculated using sensor radiance and TOA reflectance (Fernández-Pacheco). MODIS is widely used for measuring air pollution, but it has a lower spatial resolution (250 m to 1 km). Aster (14m) has higher spatial resolution but lower temporal resolution (Techarat, 2014).

After processing remote sensing images, "atmospheric path radiance"values were collected for the ground station places. Then the algorithm of pollution mapping was derived utilizing both ground station data and "atmospheric path radiance" data using Multiple Linear Regression (MLR) model in R (Zhang et. al. 2018).

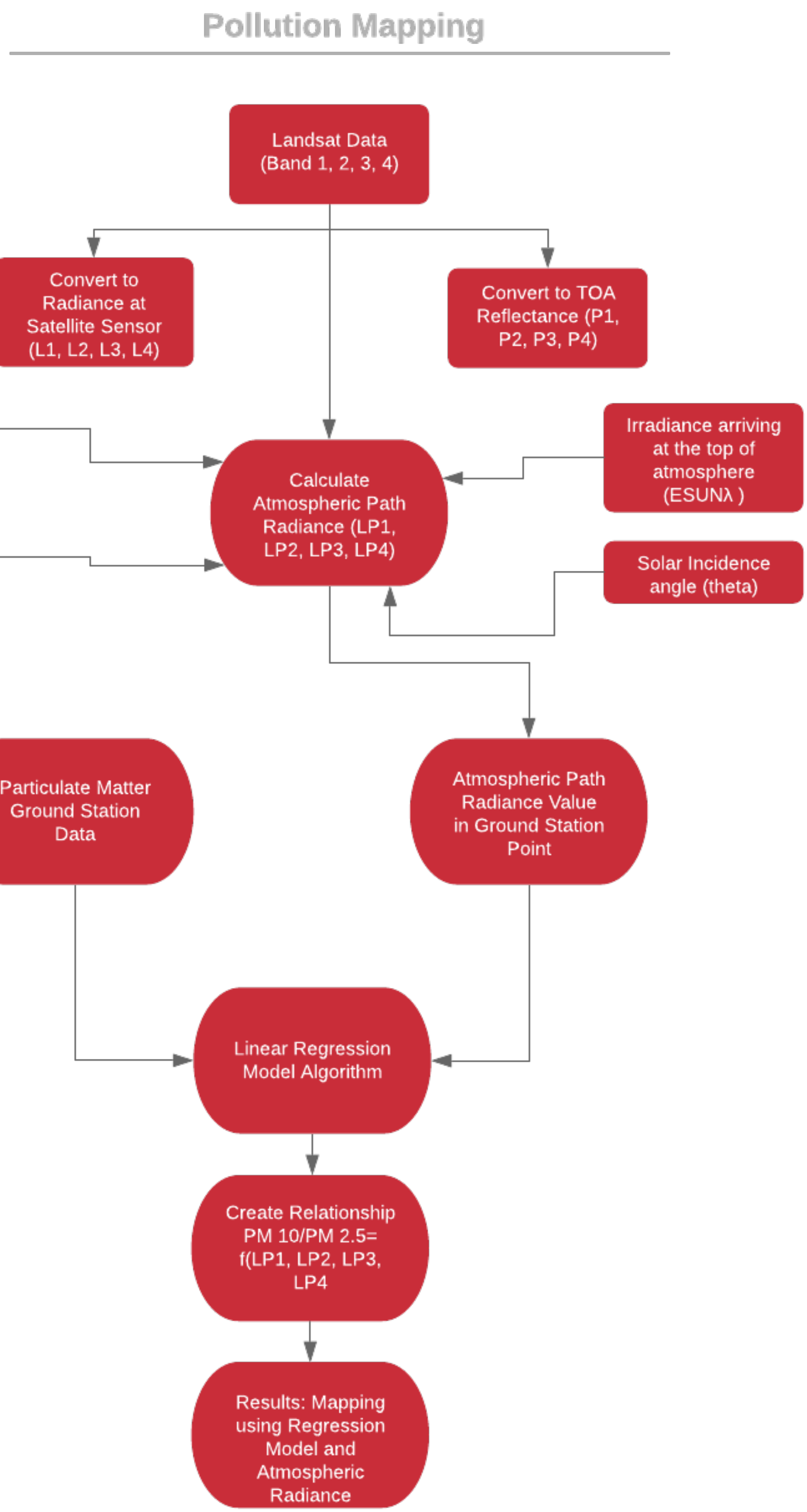


Figure 3.1: Flow Chart of Pollution Mapping

3.4.2 Measuring Air Pollution (Particulate Matter (PM) Concentration)

To measure particulate matter concentration, it is needed to measure the atmospheric path radiance or Aerosol Optical Thickness (AOT) from the satellite images. A lot of studies used AOT to measure particulate matter concentration, but this study has used atmospheric path radiance. Measuring AOT requires solving more equations comparing to atmospheric path radiance. More equations require more input parameters and is susceptible to more errors (Techarat et. al. 2018).

Techarat et al. (2018) used two concepts: dark pixel concept and atmospheric correction concept to measure atmospheric path radiance. Dark pixel was used to select suitable Landsat bands. Techarat et. al. (2018) experimented on band 1, band 2, band 3 and band 4 for measuring particulate matter of Saskatchewan, Canada. They found small degree of autocorrelation between band 3 and band 4 values and strong statistical significance of band 3 and band 4 in measuring PM10 and PM2.5. Roy et. al. (2017) used band 1, band 3 and band 4 for measuring particulate matter of Vadodara, Gujrat, India and found strong statistical significance of these bands in measuring PM10. Schiebe et. al. (1992) also used band 1, band 2, band 3 and band 4 for measuring atmospheric path radiance from Landsat MSS data. In our study, band 1, band 2, band 3 and band 4 has been used based on the findings of previous literatures.

Another concept of measuring particulate matter concentration was atmospheric correction concept which is necessary to remove noises caused by scattering process. When spectral energy interacts with PM or SO_2, then scattering happens. Concentration of PM or SO_2 defines the amount of spectral energy employed. From this idea, PM or SO_2 is measured from scattered energy (atmospheric path radiance) (Techarat et. al. 2018).

3.4.3 Measuring Atmospheric Path Radiance

The potential of atmospheric path radiance to measure particulate matter concentration depends on its principal. Sun is the major source of energy for Landsat. Sun radiance passes through the atmospheric layers, particles and gas molecules to hit different target objects. When it hit the objects, some radiance is absorbed by the object and some are reflected. Amount of reflected radiance vary based on the properties of the object or landscapes. The reflected radiance goes through the atmosphere on the top. Some of these reflected radiances are absorbed and scattered by different gas molecules and particulate matter exist in the atmosphere above the object. These absorbed and scattered radiance are called atmospheric path radiance. The rest of the radiance hit the sensor of the satellite and produce Landsat data (Techarat et. al. 2018).

The value of atmospheric path radiance is determined by following formula

Atmospheric path radiance = $\frac{\boldsymbol{\rho\lambda * ESUN\lambda * (cos(\theta))^2}}{\boldsymbol{\pi * d^2}}$ (Tesarat et. al. 2018)

Where,

Pλ is TOA reflectance with a correction for the sun angle (TOA planetary reflectance)

$$\frac{\boldsymbol{\pi * \mathrm{L}\lambda * d^2}}{\boldsymbol{ESUN\lambda * Cos\theta_S}}$$

Landsat 8 TOA reflectance will be the same whether calculated based on the standard TOA equation using the ESUN values or with the Landsat 8 Conversion TOA Reflectance equation (shown near bottom of page which does not include ESUN values but has them embedded in the equation) (GIS AG Maps). That's why, P_λ has been calculated using the following formula.

P_λ is surface reflectance of band λ. $\mathbf{P\lambda = M\rho \ * \ Qcal \ + \ A\rho}$

Where,

$\boldsymbol{\rho_\lambda}$ = TOA planetary reflectance, without correction for solar angle. Note that $\rho\lambda'$ does not contain a correction for the sun angle.

$\boldsymbol{M_\rho}$=Band-specific multiplicative rescaling factor from the metadata

$\boldsymbol{A_\rho}$ =Band-specific additive rescaling factor from the metadata

$\boldsymbol{Q_{cal}}$ = Quantized and calibrated standard product pixel values (DN)

And

L_λ is at sensor radiance for band= $\boldsymbol{ML * Qcal + AL}$

Where,

ML = Radiance multiplicative scaling factor for the band

AL = Radiance additive scaling factor for the band

Qcal = Level 1-pixel value in DN

d is correction factor for Earth-sun Distance=$\boldsymbol{1 + 0.01674\, Sin(2\pi(j - 93.5)/365)}$

ESUNλ is needed to measure atmospheric path radiance. ESUNλ=irradiance arriving at the top of atmosphere.

ESUNλ values for Landsat 8 satellite are given below

Table 3.7: ESUNλ values for Landsat 8 bands (GIS AG Maps)

Landsat 8 Bands	ESUN TOA
1	1857
2	2067
3	1893
4	1603

θ is Solar Incidence angle

$\boldsymbol{cos(\theta) = Sin(l)Sin(\delta)cos(\beta)cos(l)sin(\delta)Sin(\beta)cos(Zs)} +$
$\boldsymbol{cos(l)cos(\delta)cos(h)cos(\beta)} + \boldsymbol{sin(l)cos(\delta)cos(h)sin(\beta)cos(Zs)} +$
$\boldsymbol{cos(\delta)sin(h)sin(\beta)sin(Zs)}$ (Kalogirou, 2014)

Where,

l=Latitude

β= Surface Tilt angle

For Dhaka, β=10 degree (Ghosh et. al. 2010)

For Kolkata, β=21 degree (Wessley et. al. 2017)

Zs=Surface azimuth angle (SUN AZIMUTH from Metadata)

δ is Declination angle $\boldsymbol{\delta} = \mathbf{23.45}\ \boldsymbol{sin}(\mathbf{360/365}(\mathbf{284}+\boldsymbol{n}))$ (Kalogirou, 2018)

n=day of the year=52

h is hour angle

h= $\mathbf{15}(\boldsymbol{LST}-\mathbf{12})$ (Kalogirou, 2018)

where, LST=Local solar time

LST= $\boldsymbol{CT}+(\mathbf{1/15})(\boldsymbol{Lstd}-\boldsymbol{Lloc})+\boldsymbol{E}-\boldsymbol{DT}$

CT=Clock Time

Lstd=Standard Meridian for Local time zone (degree west)

Lloc=Longitude of actual location

E=equation of time

E=$\mathbf{0.165}\boldsymbol{Sin}\mathbf{2}\boldsymbol{B}-\mathbf{0.126}\boldsymbol{CosB}-\mathbf{0.025}\boldsymbol{SinB}$

B=$((\mathbf{360}(\boldsymbol{n}-\mathbf{81}))/\mathbf{364}$

n=day of year

3.4.4 Measuring Final Pollution Algorithm

After measuring the atmospheric path radiances of four bands, Multiple Linear Regression (MLR) was used to develop the algorithm of pollution in statistical computing programming language and software "R". intercepts, coefficients and R_2 value of every analysis were derived and final algorithm was developed. A series of statistical testing were done to the algorithms (e.g. multicollinearity, autocorrelation).

Regression Model: The regression model is a statistical model that allows someone to examine the relationship between two or more variables. Typically, in a regression model, there is one dependent variable that someone wants to predict and one or more independent variables that also called predictor (Bai, 2006). In this study, air pollution will be used as the dependent variable for regression where the band's atmospheric path radiances will be used as observations. Again, different economic sectors and determinant factors will be used as an independent variable (Wang, 2015).

MLR is slightly different from linear regression. It makes the correlation between dependent variable with multiple independent variable. MLR considers more than one determinant to predict the dependent variable. The model can be represented as a mathematical equation given below:

$$\boldsymbol{Y = A + Bx1 + Cx2 + Dx3 + \cdots}$$

Where, y is the dependent variable

A is the intercept of the model

B, C, D are the coefficient of variables x_1, x_2 and x_3 respectively.

For linear regression, standard number of subjects per variable is regarded as 10 as a thumb rule. Austin and Styerberg (2015) found that, even two subjects per variable can give a good regression result. Vittinghoff and McCulloch (2007) also found that, results of regression were acceptable even after having less than 10 EVP (Events per Predictor Variable). Normality test of the data have checked using skewness and kurtosis.

R^2 value determines the goodness of fit of the regression algorithm. The value denotes the percentage of variance of dependent variable that is explained by the independent variables. For example, 0.75 R^2 value means, on that specific regression model, 75% variance of the dependent variable can be explained by the independent variables (Wang, 2015).

3.5 Limitation of the research:

For Dhaka, PM 2.5 data were available for only three stations from the monthly report of CASE project. Inn 2014, CASE project was the only source for pollution data. Ground stations outside the study area but in the same Landsat satellite image were taken for better data representation.

Dhaka US Consulate air pollution data bank and Berkeley Earth both provided data only for PM 2.5. These two sources have been producing data from 2016 and 2018 respectively. For 2018, pollution data for Dhaka were collected from all three sources. In 2014, only 6 variables (ground station point data) were available. In 2018, there were 10 variables.

For Kolkata, WBPCB and OGD provide data only for PM 10. PM 2.5 data were available only in some station. These two sources provide data since 2001. There were other data sources like US consulate and Berkley Earth who provide PM 2.5 data and only from 2016. In this study, pollution mapping has done for 2014 and 2018. To maintain synchronization and consistency, PM 10 data has used for pollution mapping of Kolkata.

Both for Dhaka and Kolkata, number of ground station point were lower as the monitoring system for air pollution in south Asian cities are not efficient. Again, the city development authority or government organizations monitoring system has inconsistency.

3.6 Results and Discussion:

3.6.1 Dhaka:

3.6.1.1 Air pollution of Dhaka in 2014

Dhaka city air pollution (Particulate Matter 2.5 concentration) were measured for year 2014 and 2018. In 2014, six ground stations data were available and used for regression analysis with the atmospheric path radiance. Table 3.8 shows the ground stations PM 2.5 values and the atmospheric path radiance values of the geographical locations of those ground stations for Dhaka in 2014. It shows that, in 2014, band 1 and band 2 had more closer data to the ground station PM 2.5. these ground station points were used as dependent variable and the atmospheric path radiances of different bands were used as independent variables.

Table 3.8: Ground station and atmospheric path radiance values of selected stations of Dhaka in 2014

Ground Station PM 2.5	Band 1	Band 2	Band 3	Band 4
75.2	78.41	71.28	57.84	45.28
91.2	80.17	73.26	60.3	49
99.1	70.88	62.06	49.5	38.87
86	85.6	80.09	67.95	57.91
113	73.04	65.07	53.02	41.7
115	81.58	75.57	62.17	51.26

Table 3.9 shows the regression statistics of the regression analysis. the multiple R and R squared (0.82) value represent the significance of the regression model. The table also shows that adjusted R square value varies a lot from the R squared value for this year. One of the reasons behind it is the lower (6) number of variables (ground station point) were available for this year.

Table 3.9: Regression Statistics of Dhaka air pollution in 2014

Regression Statistics	
Multiple R	0.908328

R Square	0.82506
Adjusted R Square	0.125299
Standard Error	14.56866
Observations	6

Thus, the statistically valid predictive regression model to measure PM 2.5 concentration for Dhaka in 2014 is

$$\boldsymbol{PM\,2.5 = 1416.88 - 60.78 * Band1 + 54.06 * Band2 - 14.55 * Band3 + 9.26 * Band4}$$

3.6.1.2 Air Pollution of Dhaka in 2018

In 2018, ten ground station data were available for pollution mapping. All ground stations in 2014 were also kept in 2018 for better comparison. Table 3.10 shows the ground stations PM 2.5 values and the atmospheric path radiance values of the geographical locations of those ground stations for Dhaka in 2018.

Table 3.10: Ground station and atmospheric path radiance values of selected stations of Dhaka in 2018

Ground Station PM 2.5	Band 1	Band 2	Band 3	Band 4
167	43.48	36.46	28.7	22.76
171	39.84	32.44	25.18	19.41
174	42.94	35.69	27.83	21.83
165	45.23	38.5	31.04	24.88
166.5	24.07	30.31	38.29	45.32
156.7	45.33	37.35	28.62	21.17
166.5	42.17	34.58	26.53	19.82
138.6	39.95	33.55	25.98	19.41

137.1	41.94	34.3	26.69	19.26
142.1	40.74	33.22	25.19	18.78

Table 3.11 shows the statistical analysis of the regression for measuring PM 2.5 concentration for Dhaka in 2018. Decent R^2 values (0.76) represent the significance of the research.

Table 3.11: Regression Statistics of Dhaka air pollution in 2018

Regression Statistics	
Multiple R	0.873681
R Square	0.763319
Adjusted R Square	0.573975
Standard Error	9.140852
Observations	10

Thus, the statistically valid predictive regression model to measure PM 2.5 concentration for Dhaka in 2018 is

$$\boldsymbol{PM\ 2.5 = 38.07 + 17.46 * Band1 - 11.68 * Band2 - 24.62 * Band3 + 22.18 * Band4}$$

3.6.1.3 Comparison of air pollution of 2014 and 2018 in Dhaka

According to National Ambient Air Quality Standards for Bangladesh, standard for PM 2.5 concentration is 65 (CASE, 2019).

Figure 3.1 shows the PM 2.5 concentration of Dhaka in 2014 and 2018. It shows that, in 2014, northern, southern and south-eastern part of Dhaka had lower air pollution (<75 µg/m3). Few areas like, new airport, old airport and areas near the CBD had pollution greater than 250 µg/m3. South western part which is mainly the older part of Dhaka has a high population density. Apart from south-eastern part, the central part which contains the CBD of the city has comparatively higher PM2.5 concentration (151 to 200 μg/m3). Few areas on western and eastern part of the city still had PM 2.5 concentration greater than 250 μg/m3. It can be because of high amount of barren land contain more sand or other particulate matter.

Figure 3.2 also shows the PM 2.5 concentration of Dhaka in 2018. The figure shows that, whole Dhaka has pollution beyond the national standard. Few areas on north-eastern, north-western and south-eastern part of the city has pollution within the range between 75 μg/m3 to 150 μg/m3. Waterbodies like Hatirjhil lake and lake at the national zoo is two areas at the center of the city having pollution below 150 μg/m3. Except these places, all areas of the city have higher PM2.5 concentration (151 to 200 μg/m3).

Comparison of these two images show that, within these four years particulate matter concentration has risen dramatically in whole areas. Areas which had pollution below national standard have experienced pollution rise by two times within this time period. According to Rahman et. al. (2019), recent unplanned infrastructure development (eg. Highway, flyovers and buildings) followed by increase of motor vehicles can be attributed as the major contributor of dramatic pollution increase in Dhaka city.

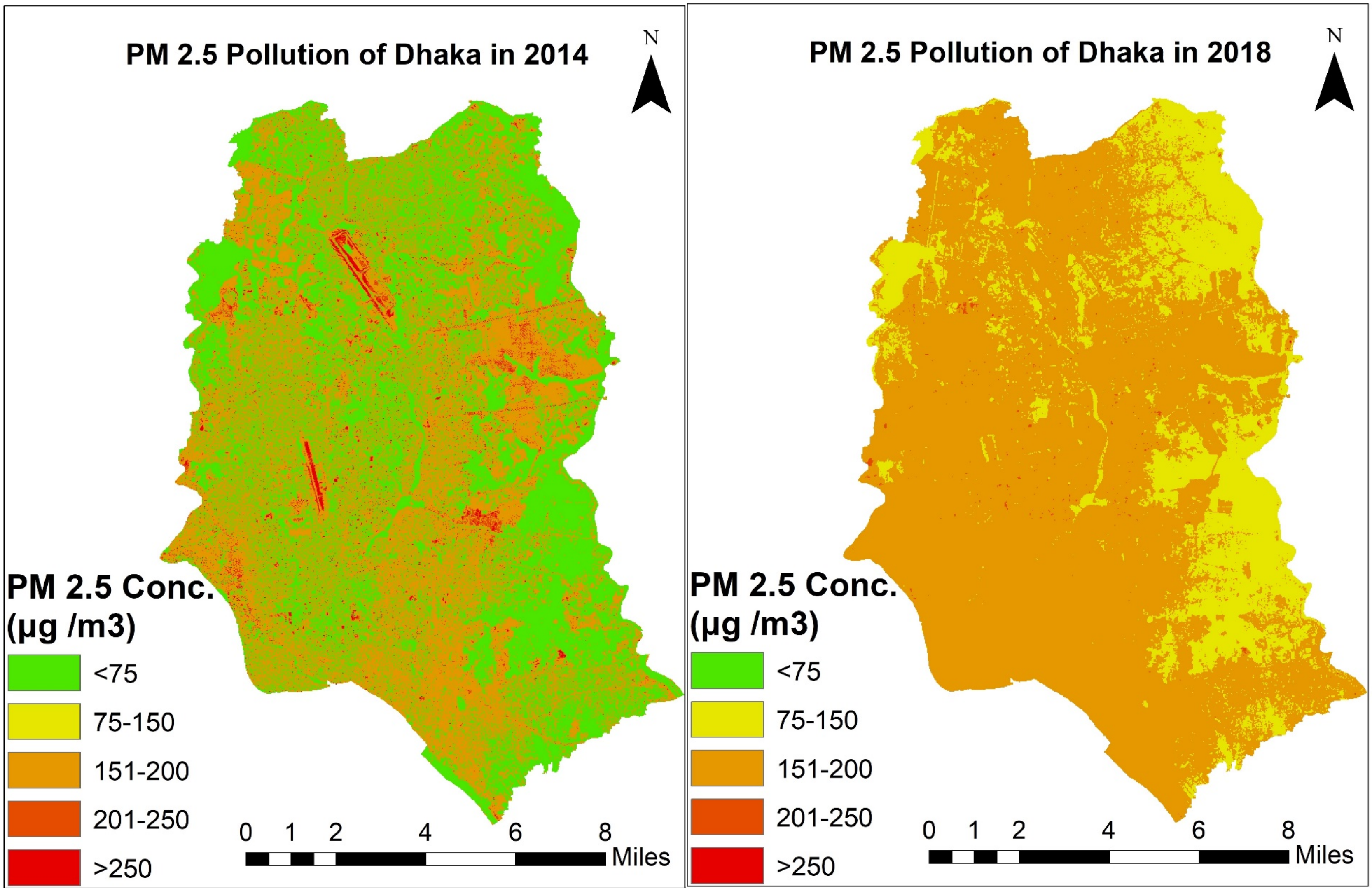


Figure 3.2: Air Pollution (PM2.5 concentration) of Dhaka city in 2014 and 2018

3.6.2 Kolkata

Air pollution (PM 10 concentration) of Kolkata has also been retrieved for the years 2014 and 2018.

3.6.2.1 Air Pollution of Kolkata in 2014

In 2014, ten ground station point data of PM 10 were available for Kolkata.

Table 3.12 shows ground stations PM 10 concentrations of Kolkata and atmospheric path radiance values for band 1, band 2, band 3 and band 4 in the respective locations of those ground control points for the year 2014. These atmospheric path radiance values were used as independent variable and ground station values were used as dependent variable for developing an algorithm to predict the PM 10 concentration of whole area for 2014.

Table 3.12: Ground station and atmospheric path radiance values of selected stations of Kolkata in 2014

Ground Station PM 10	Band 1	Band 2	Band 3	Band 4
153	55.33	48.89	38.69	32.93
45	52.28	45.41	38.4	31.89
92	50.39	43	32.18	24.39
123	56.2	49.89	42.58	35.84
140	50.8	42.98	33.44	26.21
206	52.32	45.08	34.62	29.17
148	53.72	46.69	36.44	29.69
101.5	54.19	47.33	38.61	32.4
154.33	53.89	46.68	37.91	30.76
145.33	51.27	43.82	34	26.36

Table 3.13 shows the statistical significance of the regression analysis to measure PM 10 concentration of Kolkata in 2014. Better R^2 (0.75) value denotes the validity of the algorithm.

Table 3.13: Regression Statistics of Kolkata air pollution in 2014

Regression Statistics	
Multiple R	0.86852
R Square	0.754326
Adjusted R Square	0.557787
Standard Error	28.96893
Observations	10

Thus, the statistically valid predictive regression model to measure PM 10 concentration for Kolkata in 2014 is

$$\boldsymbol{PM\ 10 = -2101.79 + 136.81 * Band1 - 92.23 * Band2 - 37.22 * Band3 + 19.45 * Band4}$$

3.6.2.2 Air Pollution of Kolkata in 2018

Most of the station used in 2014 were kept in 2018 also for better comparison of the models.

Table 3.14: Ground station and atmospheric path radiance values of selected stations of Kolkata in 2018

Ground Station PM 10	Band 1	Band 2	Band 3	Band 4
156.67	57.54	49.62	37.53	28.83
98.33	58.11	50.31	39.11	30.78
121.67	54.76	46.21	35.1	26.5
97.33	56.54	48.84	38.15	30.1
119.33	53.8	45.7	34.22	26.34
129.33	55.75	47.83	36.2	28
124.33	55.74	47.84	36.23	27.5
131.33	55.74	47.56	35.83	27.57
97	55.78	47.71	36	27.4

104	55	46.9	36	29.4
92	54.03	45.9	34.84	26.55
132.33	57.72	49.45	38.33	29.3

Table 3.14 shows ground stations PM 10 concentrations of Kolkata and atmospheric path radiance values for band 1, band 2, band 3 and band 4 in the respective locations of those ground control points for the year 2014.

Table 3.15 shows the statistical significance of the regression analysis to measure PM 10 concentration of Kolkata in 2014. This algorithm has a little bit lower R^2 value (0.58) which means that, 58% variance of the final PM 10 concentration are explained by the atmospheric path radiances of four bands in respective ground station point locations.

Table 3.15: Regression Statistics of Kolkata air pollution in 2018

Regression Statistics	
Multiple R	0.759879
R Square	0.577417
Adjusted R Square	0.33594
Standard Error	15.8787
Observations	12

Thus, the statistically valid predictive regression model to measure PM 10 concentration for Kolkata in 2018 is

$$\boldsymbol{PM\ 10 = -791.59 + 38.38 * Band1 - 1.06 * Band2 - 34.95 * Band3 + 3.16 * Band4}$$

3.6.2.3 Comparison of air pollution of 2014 and 2018 in Kolkata

In India, daily average PM 10 concentration standard is 100 µg/m3 (Das et al. 2015). Kolkata is among the highly polluted cities because of its high rate of Solid Particulate Matters (SPM) and

PM10 levels (Gurjar et. al. 2016). Figure 3.3 shows the PM 10 concentration of Kolkata in 2014 and 2018.

Figure 3.3 shows that, in 2014, most of the areas of KMA except the central part had PM 10 concentration below 65 µg/m3. According to the land cover classification, urban growth of Kolkata expanded across the Hooghly river to the other side. The PM 10 concentration also followed the same trend and path. CBD area of Kolkata had the highest PM 10 concentration (greater than 250 µg/m3). Areas surrounding CBD area has pollution between 65 to 150 µg/m3. Some areas on the farthest northern part of KMA has also PM10 concentration beyond 250 µg/m3.

In 2018, domain of pollution in Kolkata had changed dramatically. There are very few areas on the southern part of KMA having pollution below 65 µg/m3. Most of the areas have PM 10 concentration between 151 to 200 µg/m3. Sahu (2019) found that increasing of motor vehicles, industrialization, thermal power plants, popularization of stubble-burning in rural areas, burning of crops, burning of waste, rapid urbanization, uncontrolled population growth and deforestation are responsible for this rapid pollution increase of Kolkata. Majumdar et al. (2020) found that domestic and commercial combustion is the major contributor of PM10 pollution. They also found that, by 2030, PM 10 can rise to 43% if the increasing rate follows present trend.

Comparing two images of 2014 and 2018, it is evident that, horizontal area under PM 10 concentration has been increased. The intensity and degree of concentration have also increased in few places near the CBD and newly transformed barren lands from greenspaces.

Air pollution has become one of the deadliest problem people of south Asia are facing (Reddy and Roberts, 2019). In recent times, these two cities have become one of the ten polluted cities for generating extreme pollution (Brauer et al. 2019). This study also found that, with the expansion of geographical and demographic boundaries of the cities along with the significance, the air pollution is also becoming a prior concern. The rate of pollution of these cities have already surpassed the benchmark of pollution fixed by their respective governments or any organizations. Research also found that, due to low density ground monitoring of pollution.

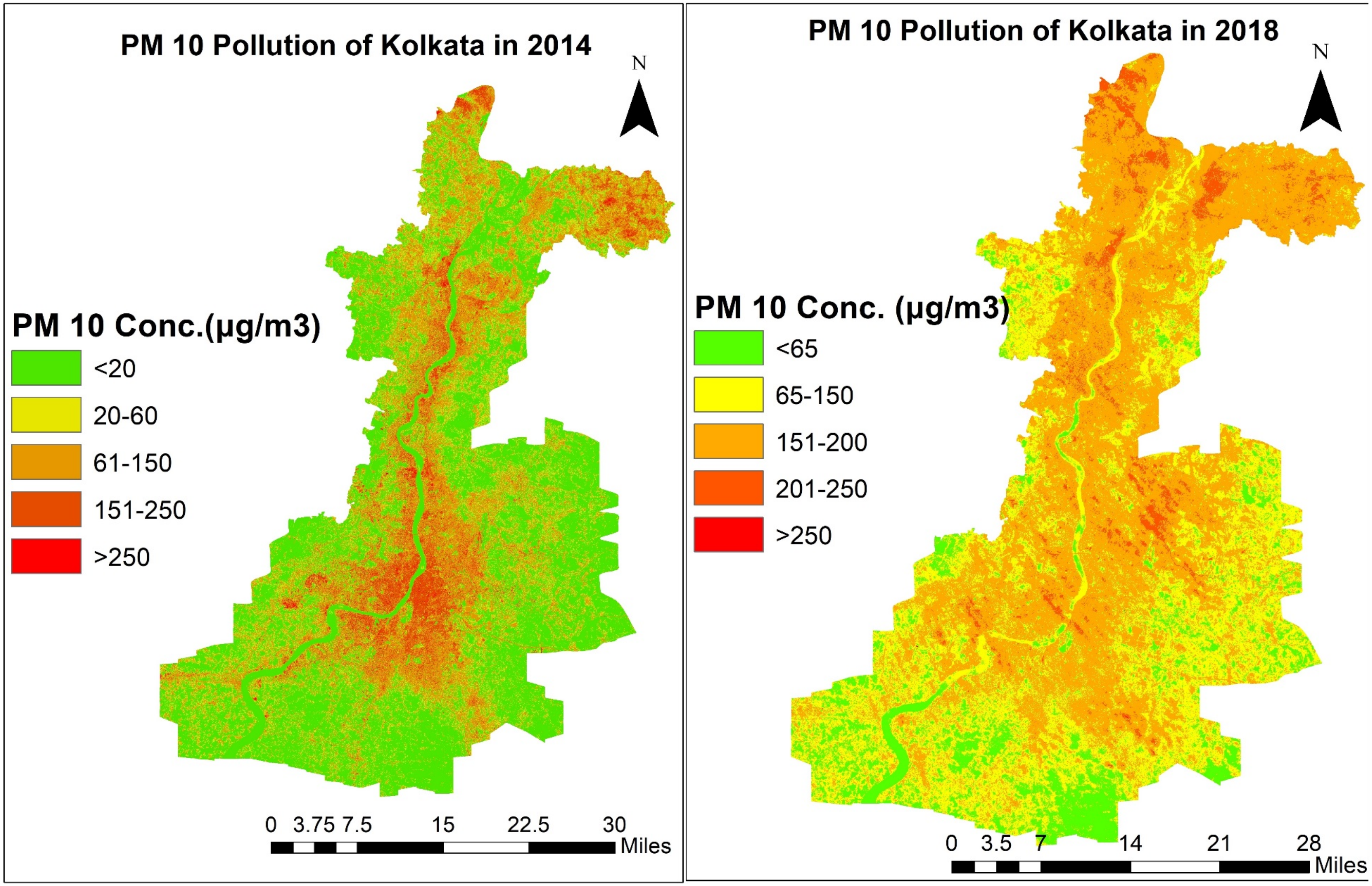


Figure 3.3: Air Pollution (PM2.5 concentration) of Kolkata in 2014 and 201

CHAPTER 4: ACCESSIBILITY TO LOWER AIR POLLUTION AREAS

4.1 Urban Natural Landscapes and Air Pollution

Urban form and landscapes of a city is instrumental for its environment and air quality. Weng and Yang (2006) tried to find out the source and mostly affected places of air pollution. They found that areas of industrial intensity, population density and commercial activities are sources of Sulpher Di Oxide (SO_2) concentration. The magnitude of higher pollution is also found within the area having these infrastructures. Highway corridors and urban street canyons are notoriously affected for severe levels of Nitrogen Oxides (NOx) (Weng and Yang, 2006). High density transportation network and places nearby are more vulnerable to these types of pollution. According to their study, road networks are the sources and affected areas of NOx pollution and high density urban/built up areas, construction sites, and closed spaced buildings are the areas suffering from dust related pollution (Particulate Matter).

Exposure of city dwellers to air pollution is one of the most common problem of urban life. Nearness to industrial and commercial hubs, high density and proximity to road networks make the urban dwellers more vulnerable to air pollution. Green spaces and green infrastructures can mitigate the pollution and decrease people's exposure to air pollution to a large scale (Kumar et al. 2019). Trees and green spaces also act as a natural filtering barrier for air pollution. Apart from vegetation, waterbody also plays an important role in decreasing pollution from particulate matter. Escape CASE study in Stockholm county found that waterbody in 500m buffer area can decrease the particulate pollution in a significant amount (Wu et al. 2015). The study also found that, though effect and significance of water is often neglected, water's contribution is inevitable for air pollution emission as it absorbs and deposits particulate matter.

4.2 Lower Pollution and Urban Dwellers Vulnerability

Open spaces and recreational public spaces are also an integral part of a city's landscape, contributing to the citizens' physical and mental wellbeing. Access to these natural landscapes also decrease people's exposure to air pollution. Some studies found that, very often, poorer people are more exposed to air pollution (Schio et al. 2019). Houston et al. (2016) found that minority and high-poverty neighborhoods are more exposed to traffic related air pollution in California, USA. However, green spaces, waterbodies and other natural landscapes work as a natural filter to air pollution and active recreation spaces need to be equally accessible to all the residents of the city. Sometimes, many factors work behind allocation and preservation of both manmade and natural open spaces. Specially in high density cities, very few people have access to these open spaces within walking distance from their homes and offices (Houston et al.2016).

4.3 Urban Natural Landscapes of Dhaka and Kolkata

Dhaka, one of the most densely populated cities in the world with 2.8% growth rate has experienced excessive decrease in green and public spaces (Hassan and Southworth, 2017). Dhaka is the also 11th largest megacity in the world, where 18.2 million people live in an area of 590 square miles (Sharmeen and Houston, 2019). A study shows that in the 1990s, Dhaka had **61%** non-urban or semi-rural, agriculture land use. It became 525 in 2013 and among these non-urban land use, only **0.30%**) of the land is used for recreational activities (Dhaka Metropolitan Development Plan (DMDP) Structure Plan, 2016). This is mostly due to population pressure and associated land demand. The other factors of limited accessibility to green parks is unplanned distribution of green open space throughout the city.

Kolkata is another high-density city of South Asia. The city has experienced rapid urban growth specially after 1975. From 1975 to 1990, growth rate for urban built up area was 57.61 and from 1990 to 2005, it increased to 64.91 (Bhatta, 2008). The city's boundaries have been expanded by 18.17% (Bhatta, 2008). From 2001 to 2018, built-up areas have been increased by 34% (Mandal et al. 2019). At the same time vegetation and waterbodies have combinedly decreased by 16% (Mandal et al. 2019). Mitra and Banerji (2018) found that, in last 16 years, only New Town of Kolkata (north eastern part) has experienced significant depletion of waterbodies. With the continuous decrease of these landscapes are decreasing people's accessibility at a large scale in all over Kolkata. West Bengal Housing Infrastructure Development Corporation (WBHIDCO) has created 1,130,000 m^2 of waterbodies but ever-increasing expansion of real estate builders demand and encroachment has made the waterbodies filled for construction in many cases. WBHIDCO is also making some parks in Kolkata to increase people's accessibility to green and natural landscapes (Mitra and Banerji, 2018).

DMDP is the guideline for land use distribution of Dhaka. According to DMDP, 1995-2015, the standard requirement for open space is 0.16 acre for 1000 people (Jafrin and Beza, 2018). DAP (Detail Area Plan)2010 proposed 10 acres of open space in neighborhood level for 12500 people (DMDP Structure Plan, 2016). For new master plan, DMDP 2016-2035 proposed 0.86-acre open space requirement for a neighborhood of 1000 people. Though the city has guidelines for open spaces, every part of it may not match the criteria. Again, some part of the city may have required open spaces but there can be lower accessibility due to inefficient road network

Kolkata currently have no policy regarding park, playground, natural landscapes and waterbodies. Recent Prospective Plan of CMA: 2025 has no direct guidelines for rules, regulations and policy for park's inclusion in city, conservation of natural landscapes and functioning of these public spaces.

This paper aims to use network analysis to find out the shortest path to the public spaces from the building blocks. It has measured the total service areas of these natural landscapes. The study has also measured accessibility based on road hierarchy to assess how many peoples are benefited by the public space. It also tells the readers how many people can go there using local road, how many with service roads and how many must use major highway. This will help in planning purposes for a more sustainable and healthy living in overpopulated cities like Dhaka and Kolkata.

4.4 Methodology

4.4.1 Data Acquisition

4.4.1.1 Satellite Images

At first, the correlation between different landcovers and pollution has been assessed to find out the general lower polluted areas of the cities. The hypothesis of this study is to see whether air pollution is greater in urban built up areas like buildings, barren lands and roads or in areas with vegetation, waterbodies and other natural landscapes. For this purpose, Normalized Difference Vegetation Index (NDVI), Normalized Difference Built up Index (NDBI) and Normalized

Difference Water Index (NDWI) layers have been made. These image layers have been derived using Landsat images. Table 4.1 represents the information of the Landsat images used for both study areas.

Table 4.1: Landsat data of Study location

Landsat Data for the Study		
City	Dhaka 2018	Kolkata 2018
Date	21-FEB-18	28-FEB-18
Path	137	138
Row	44	44

4.4.1.2 GIS Shapefiles

Road network data for this study have been collected from open street map (OSM) (source: http://download.geofabrik.de/).

4.4.1.3 Demographic Data

For the third research question, demographic characteristics of the city has been collected. The city shapefile has been collected in ward (smallest statistical unit available for Dhaka) level (BBS, 2010). The collected data regarding demographic characteristics are i) population density and ii) percentage of poor.

4.4.2 Non-spatial Correlation

Particulate Matter Pollution:

Non-spatial correlations between cities air pollution and land covers have been done. For air pollution particulate matter concentration has been used. Air pollution increase is one of the inevitable impacts of landcover changes in south Asia where, particulate matter concentration has become one of the major contributor of cities pollution (Brauer et al. 2019). Particulate matter concentration often defines the cities degree of health too (Balakrishnan et al. 2019).

In this study, Particulate Matter (PM) 2.5 pollution was measured for Dhaka and Particulate Matter (PM) 10 pollution was measured for Kolkata. Both types of data were not available for selected study years for both the cities. Data has been used based on the availability.

PM 2.5 is Particulate matter with aerodynamic diameter < or = 2.5 micrometer

PM 10 is Particulate matter with aerodynamic diameter < or = 10 micrometer

PM 2.5 is finer than PM 10 and more detrimental to health. Both types of particulate matter go through human's breath and do respiratory illnesses. That's why, cities environmental quality largely depends on the concentration of these particulate matters (Schwartz et al. 2002)

NDVI has the following formula (Ke et al. 2015)

$$\boldsymbol{NDVI} = (\boldsymbol{NIR} - \boldsymbol{RED}/\boldsymbol{NIR} + \boldsymbol{RED})$$

where *RED* and *NIR* are TOA or surface reflectance at red and near-infrared band, respectively.

The NDVI value varies from -1 to 1. Higher the value of NDVI reflects high Near Infrared (NIR), means dense greenery. Generally, we obtain following result:

NDVI = -1 to 0 represent Water bodies

NDVI = -0.1 to 0.1 represent Barren rocks, sand, or snow

NDVI = 0.2 to 0.5 represent Shrubs and grasslands or senescing crops

NDVI = 0.6 to 1.0 represent Dense vegetation or tropical rainforest

NDBI is retrieved using the following formula (Zha et al. 2003)

$$\boldsymbol{NDBI} = (\boldsymbol{SWIR} - \boldsymbol{NIR}/\boldsymbol{SWIR} + \boldsymbol{NIR})$$

where *SWIR* and *NIR* are TOA or surface reflectance at shortwave infrared and near-infrared band, respectively.

The Normalize Difference Build-up Index value lies between -1 to +1. Negative value of NDBI represent water bodies whereas higher value represents build-up areas. NDBI value for vegetation is low.

NDWI is retrieved using the following formula (Gao, 1996)

$$NDWI = \ (NIR - SWIR/NIR + SWIR)$$

where *SWIR* and *NIR* are TOA or surface reflectance at shortwave infrared and near-infrared band, respectively.

Normalize Difference Water Index (NDWI) value lies between -1 to 1. Generally, water bodies NDWI value is greater than 0.5. Vegetation has much smaller values which distinguishing vegetation from water bodies easily. Build-up features having positive values lies between 0 to 0.2.

To check the correlation of different landscapes and air pollution of the city, correlation analysis was executed in R programming language. For the correlation analysis, the raster file of NDVI, NDBI, NDWI and pollution map were converted into ASCII format in Erdas Imagine. It was then transformed into text file and further processed by appending the row number at the beginning of each row. Every time, two raster images were taken and merged and converted into ASCII format (Figure 4.1).

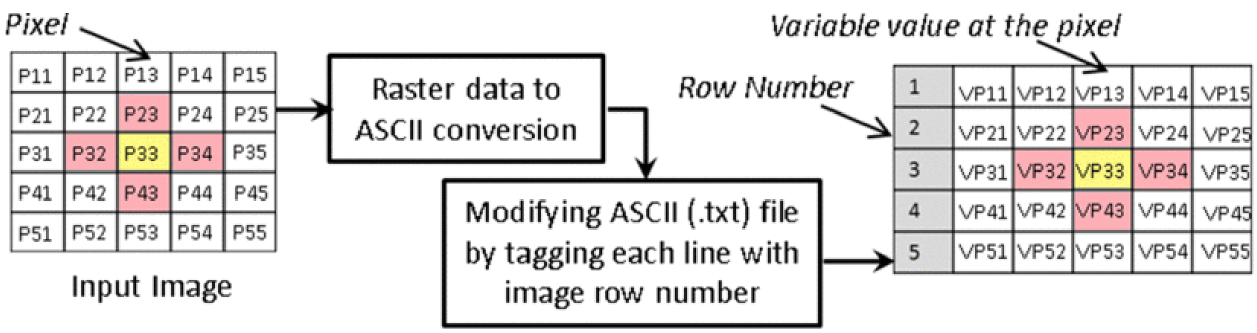


Figure 4.1: Raster data to ASCII format (Das et al. 2017)

That ASCII file was converted into text file. In the text file, there were two rows, one for pollution and another for either NDVI, NDBI or NDWI. These rows contained the pixel value of respective image in each point. The null values and missing values were filtered by filtering tool in RStudio. Then the correlation analysis was made to run. In each analysis, about 3.6-million-point data were used to measure the correlation analysis and trend line. The summary of the correlation value gives the R^2 value. The graphs of correlations were also generated.

4.4.3 Network Analysis:

The first two research questions are concerned about public open space and accessibility through road hierarchy. For selecting natural landscapes, parks, playgrounds, gardens, zoo, waterbodies and public cemeteries having an area of 0.86 acres (3480 sq. m) have been considered. As 0.86 acres is the requirement for 1000 people, it has been selected as the criteria of this study assuming 1000 people make the smallest neighborhood in Dhaka and Kolkata. Dhaka has a structure plan describing minimum area allocation for natural landscapes, but Kolkata has no guideline. As these two cities have similar physical and demographic characteristics, in this study the DMDP guidelines are used for Kolkata too. There are 15 types of roads in OSM data. Those roads have been reclassified into three types of roads based on their width and services. The reclassified road types are i) primary, ii) secondary and iii) tertiary.

Different types of roads from OSM data has been classified into these three types of roads. The classification of those roads their functions are given in table 4.2.

Table 4.2: Types of roads and functions from OSM (Open Street Map) data

Road types	Road types from OSM	Functions
Primary	Bridleway	Paths for horse riding
	Cycleway	Paths for cycling
	Footway	Footpath
	Living street	Streets where pedestrians have priority
	Path	Unspecified paths
	Pedestrian	Pedestrian only streets
	Residential	Roads in residential areas
	Steps	Flights of steps on footpaths
	Service	Service roads for access to buildings, parking

		lots, etc.
Secondary	Track	For agricultural use, in forests, etc. Often gravel roads.
	Track grade 1	Tracks can be assigned a “tracktype” from 1
	Unclassified	Smaller local roads
	Unknown	Unknown type of road or path
	Secondary	Secondary roads, typically regional.
	Secondary link	Highway link from secondary roads
Tertiary	Primary	Primary roads, typically national (Major roads)
	Primary link	Highway link
	Tertiary	Tertiary roads, typically local (Major roads)
	Trunk	Important roads, typically divided (Major roads)
	Trunk link	Roads that connect from one road to another of the same of lower category.
	Motorway	Motorway/freeway

In network analysis, green spaces and waterbodies were used as facilities (destination). Buildings were selected as origin of the analysis.

In OSM, different types of greenspaces and waterbodies exists. Following are the examples of origin and destinations of the network analysis.

Facilities: Castle, fort, garden center, graveyard, park, picnic site, playground, stadium, theme park, zoo, botanical garden

Origin: Buildings

Any facilities which are not less than 0.86 acres, were selected as facilities or destination places for people.

For accessibility, the study selected 400-meter (0.25 miles) areas as service area. The service area of these open spaces refers the extent of area it is serving.

The study considered service areas based on walking distance. All people in a neighborhood including aged and children must have access to the nearest open spaces. As a result, 400 meters has been selected as the criteria for service area. Average walk trips of Dhaka are 15 minutes where people walk at a speed of 5 km/hour (Sharmeen and Houston, 2019). Based on that information, 5-minute walking distance has been derived.

Then a network dataset has been made using modified OSM street shapefile. Based on that network dataset, service areas have been made. From OSM data, Polygon files of green spaces and waterbodies have been merged and then converted to point file. For converting, the study used "densifying the geometry" method of QGIS. Centroid point-based conversion was avoided as it sometimes leaves the service areas beyond 400 meter of the public spaces if the public space itself has an area more than 400 meter. Break point for service area measurement was taken as 400 meters.

4.4.4 Accessibility Mapping

After measuring the service area for all types of roads, service areas were divided into three types. Service areas accessible by i) primary roads, ii) secondary roads and iii) tertiary roads. Service areas were used as target layer feature and road types were used as source layer feature. Service areas "touch the boundary of the source (either primary, secondary or tertiary road) layer feature" were selected using "select by location" tool of ArcGIS. Service areas touch primary roads, secondary roads and tertiary roads were termed as i) primary service areas, ii) secondary service areas and iii) tertiary service areas respectively.

Another "select by location" operation was executed to distinguish the buildings of specific service areas. Selected "service areas" then used as source layer and "buildings" shapefiles were used as target layer feature. Buildings are "completely within the source layer feature" were selected afterwards. Buildings are completely within i) primary service areas, ii) secondary service areas and iii) tertiary service areas were selected. Thus, the buildings having accessibility to service areas (facilities) through i) primary roads, ii) secondary roads and iii) tertiary roads were retrieved (Lin et. Al. 2019). The percentage of buildings having access to nearest public open space using different roads have been measured using data of attribute table.

4.4.5 Correlation Analysis

Correlation analysis between hierarchical accessibility and people's demographic characteristics was performed. Local spatial autocorrelation method was used for this study. Both Univariate Local Moran's I and Bivariate Local Moran's I methods were used.

Demographical data of Kolkata were unavailable, so correlation analysis was performed only for Dhaka. The correlations between

i) Correlations between service areas
ii) Correlations between service areas and Percent of poor
iii) Correlations between population density and Percent of poor

Were done using GEODA software.

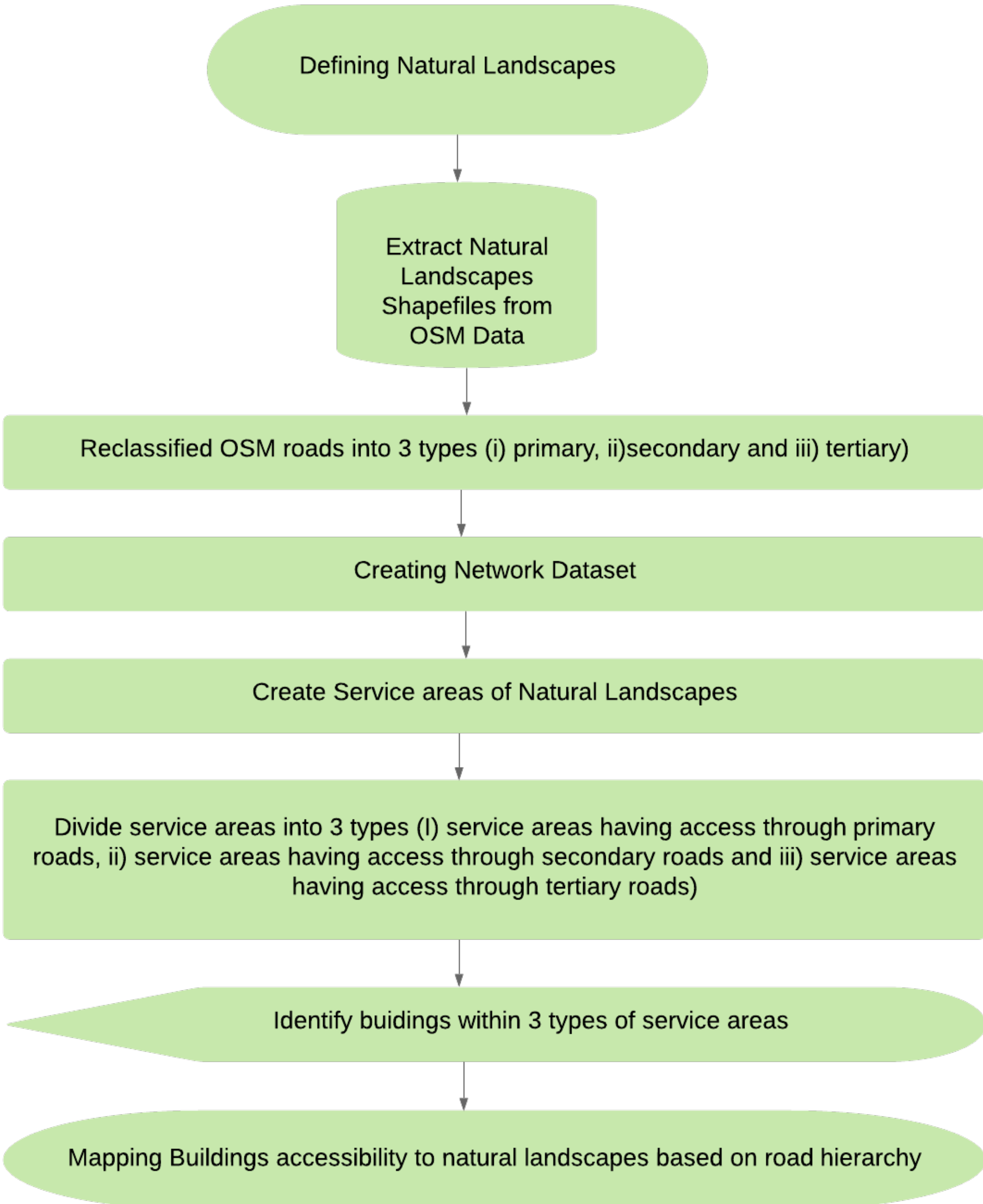


Figure 4.2: Flow Chart of Accessibility Analysis

4.5 Results and Discussion

4.5.1 Dhaka:

4.5.1.1 Correlation Analysis Between Landscapes and Air Pollution

PM 2.5 pollution and NDVI:

PM 2.5 pollution of Dhaka and NDVI of Dhaka is negatively correlated. Figure 4.3 represents the PM 2.5 pollution map and NDVI map of Dhaka for the year 2018. The map shows that, air pollution is higher mainly in the central places of Dhaka where the density of built-up areas is higher. NDVI values in those places are also negative. On north-eastern and south-eastern part of Dhaka, NDVI value is higher and positive, similarly pollution on those areas is comparatively lower.

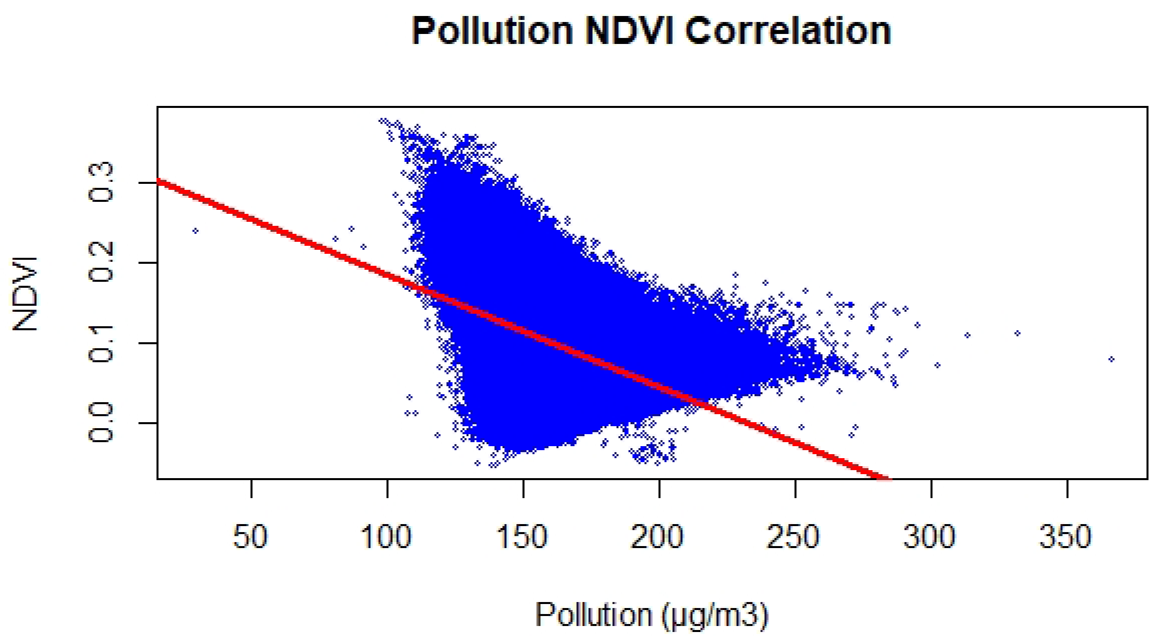


Figure 4.2: Correlation between PM 2.5 pollution and NDVI for Dhaka in 2018

Negative correlations between PM 2.5 pollution and NDVI values for Dhaka is represented in figure 4.2. The R^2 value of this correlation is **-0.52** that means that, 52% variations of pollution are explained by NDVI values. So, significantly, where the pollution is higher, NDVI values are lower.

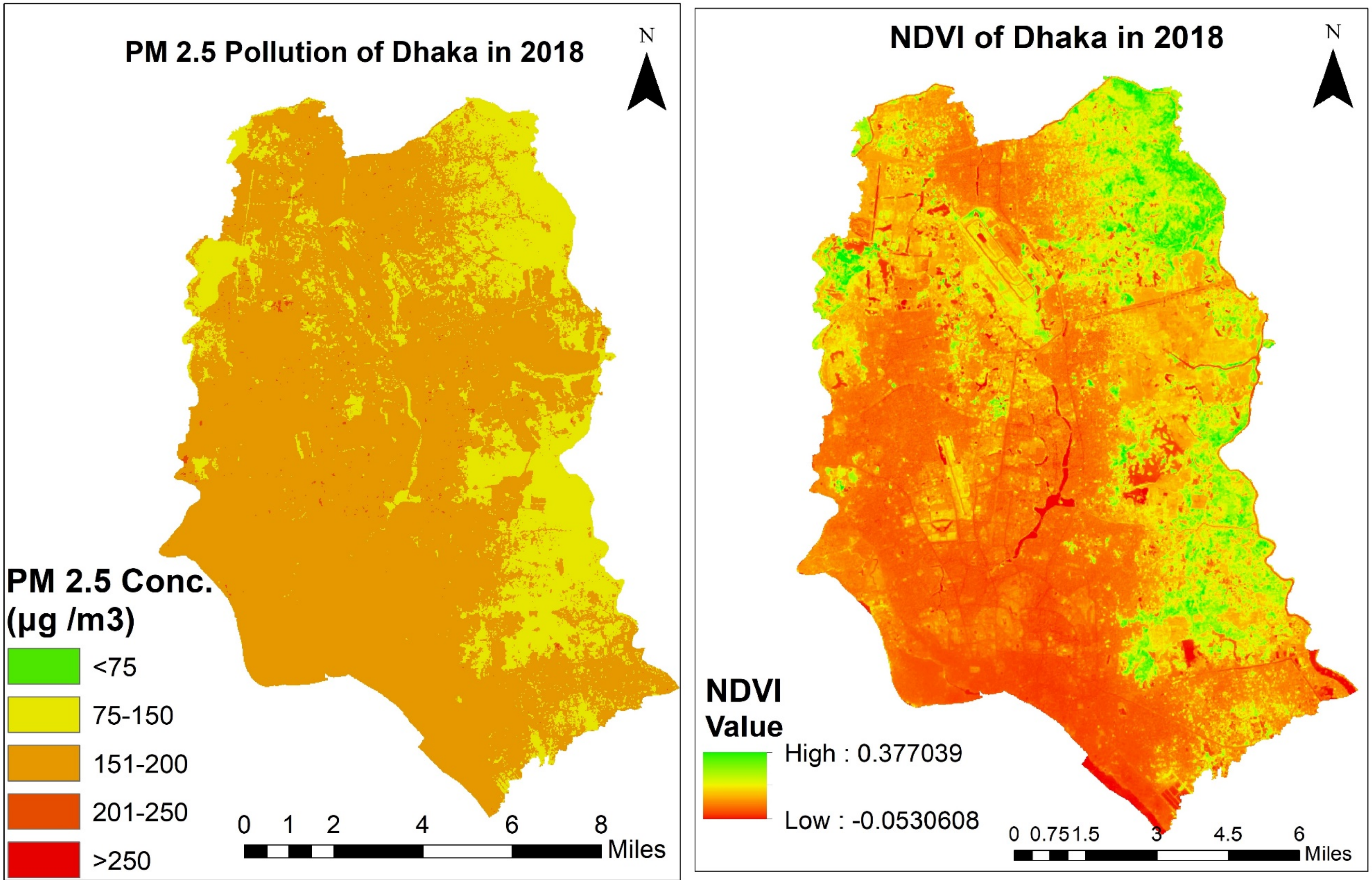


Figure 4.3: PM 2.5 pollution and NDVI map of Dhaka in 2018

PM 2.5 Pollution and NDBI:

PM 2.5 pollution and NDBI values of Dhaka are also highly correlated. Figure 4.5 shows that, NDBI values are lower in north-eastern and south-eastern part of Dhaka which areas also have lower pollution rate. One small part in north western part of Dhaka has also negative and lower value which also matches the lower pollution rate geographically. North-western, eastern and central part of the city has higher NDBI values as these places have high-density built-up areas and barren lands which are source of pollution. PM 2.5 pollution rate is also higher in these areas.

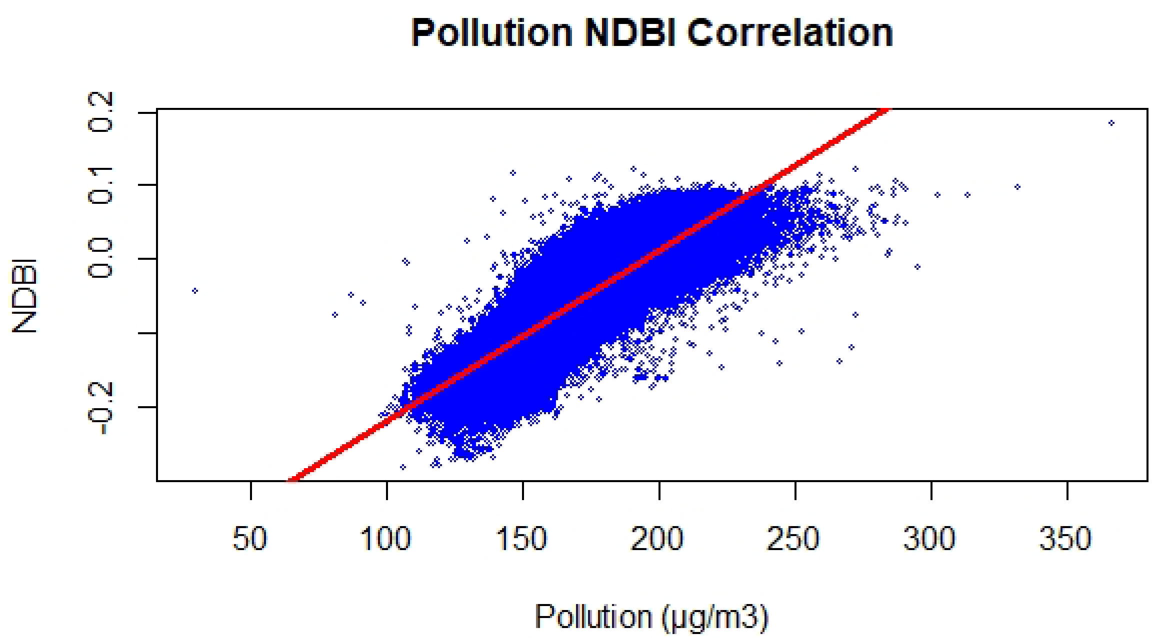


Figure 4.4: Correlation between PM 2.5 pollution and NDBI for Dhaka in 2018

Positive correlations between PM 2.5 pollution and NDBI values for Dhaka is represented in figure 4.4. The distribution of data and trendline shows that, these values have a positive correlation which means, where pollution is higher, NDBI values are also higher. The R^2 value of this correlation is **+0.88** that means that, 88% variations of pollution are explained by NDBI values

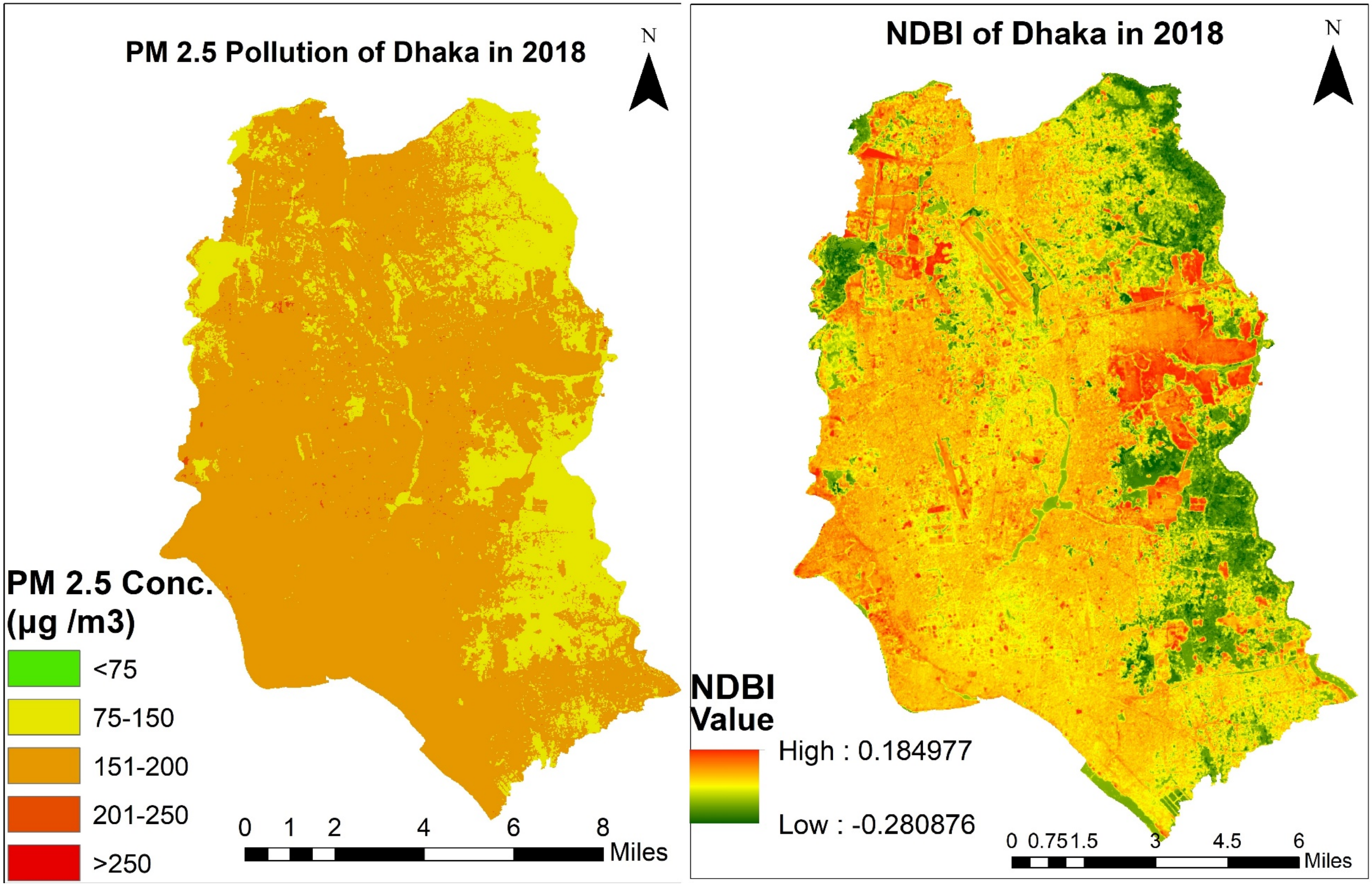


Figure 4.5: PM 2.5 pollution and NDBI map of Dhaka in 2018

PM 2.5 Pollution and NDWI:

PM 2.5 pollution and NDWI has also significant relations. Figure 4.7 represents the PM 2.5 pollution map and NDWI map of Dhaka for the year 2018. The map shows that, air pollution is higher mainly in the central places of Dhaka where the density of built up areas are also higher. NDWI values in those places are also negative. On north-eastern and south-eastern part of Dhaka, NDWI value is higher and positive, similarly pollution on those areas is comparatively lower. Though NDWI value of Dhaka don't have a high range for the quality of waterbodies, still NDWI value has strong correlation with PM 2.5 pollution.

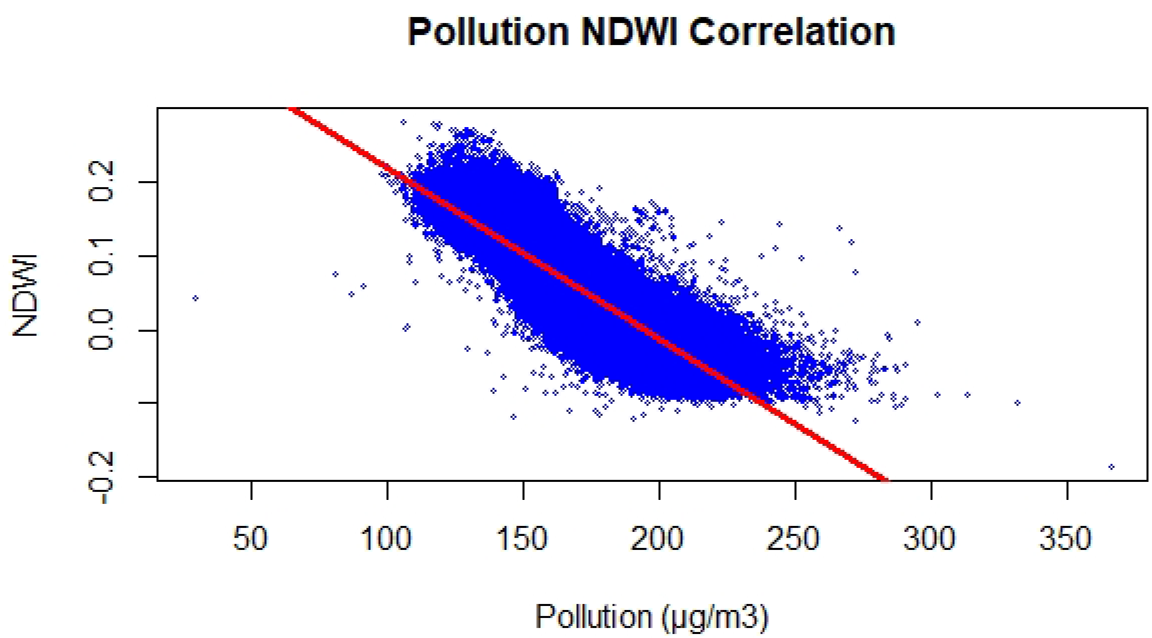


Figure 4.6: Correlation between PM 2.5 pollution and NDWI for Dhaka in 2018

Negative correlations between PM 2.5 pollution and NDWI values for Dhaka is represented in figure 4.2. The distribution of data and trendline shows that, these values have a negative correlation which means, where pollution is higher, NDWI values are lower. The R^2 value of this correlation is -0.88 that means that, 88% variations of pollution are explained by NDWI value.

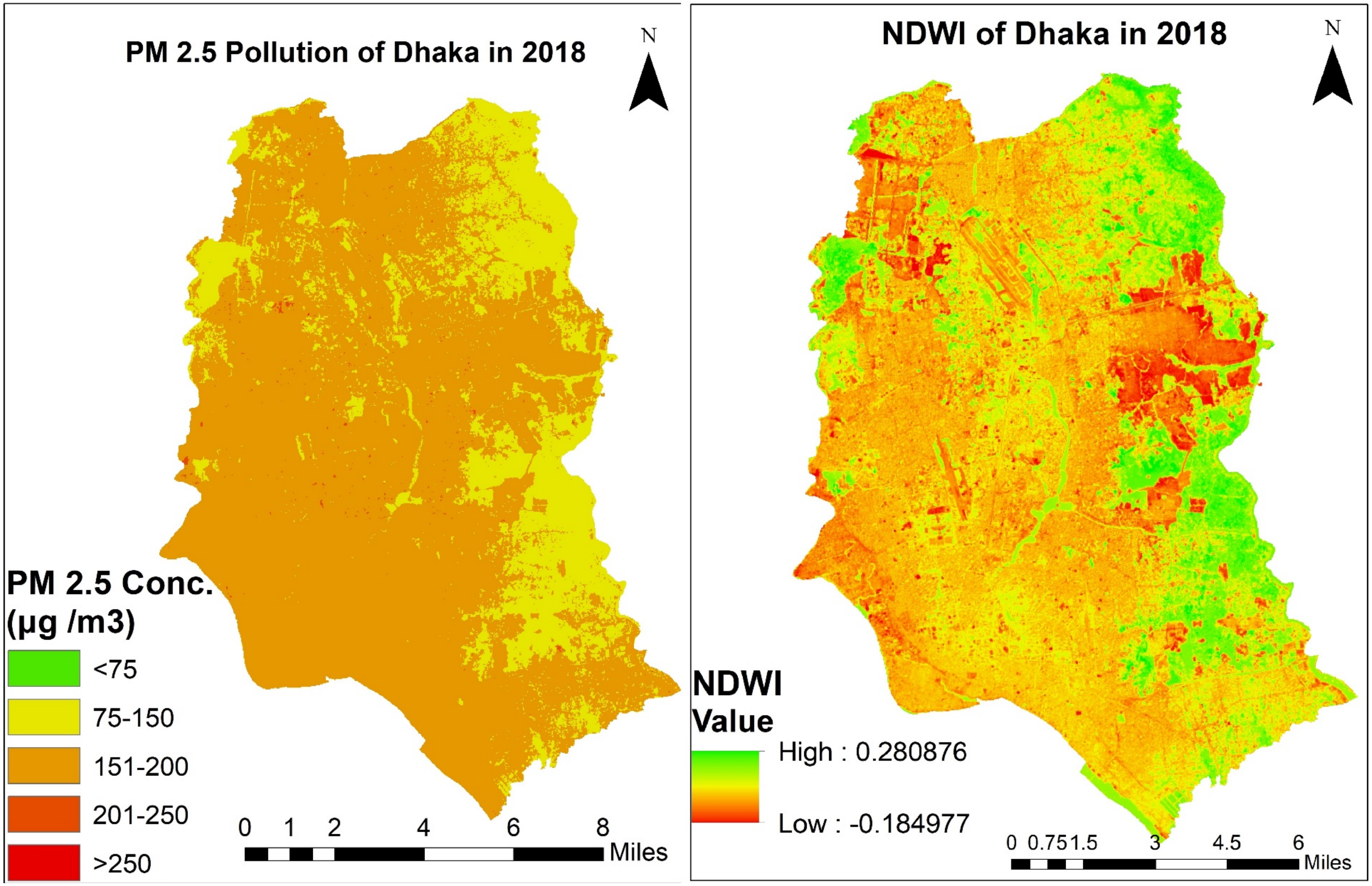


Figure 4.7: PM 2.5 pollution and NDWI map of Dhaka in 2018

4.5.1.2 Measurement of Accessibility to Public Open Space

Service area:

Service areas of the public open spaces of Dhaka is shown in figure 4.7. The service areas covered almost 46% areas of Dhaka city. The figure represents that, service area of all green spaces and waterbodies are distributed all over the city.

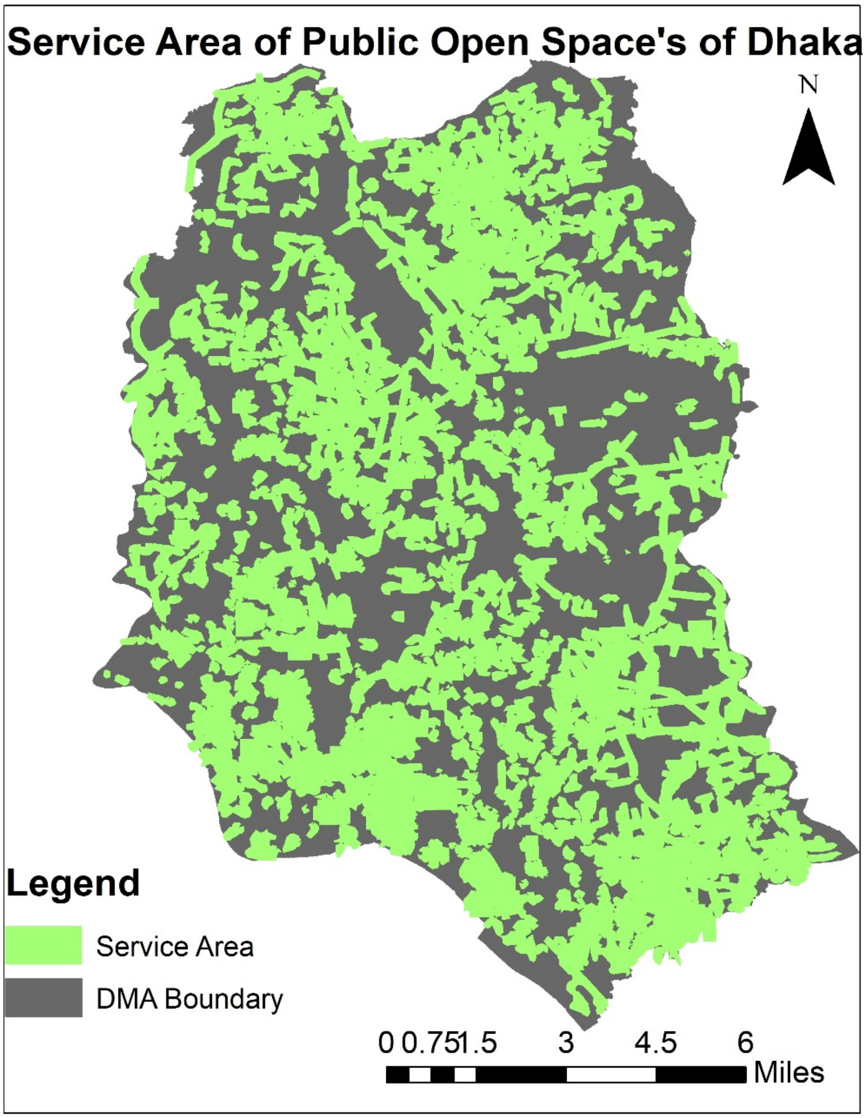


Figure 4.8: Service area of natural landscapes

In this study, green spaces and waterbodies have taken from OSM data which is not real time data. These areas are not officially recognized as public areas by the government rather all the green spaces and waterbodies have taken into consideration in this study. There may be some green areas and waterbodies which are not functioning well, or which is restricted for common people to go.

Figure 4.9 represents the road networks of Dhaka. It shows that, in Dhaka the share of primary roads is significantly higher than secondary and tertiary roads. This can be one reason of 46% areas of the city under service areas.

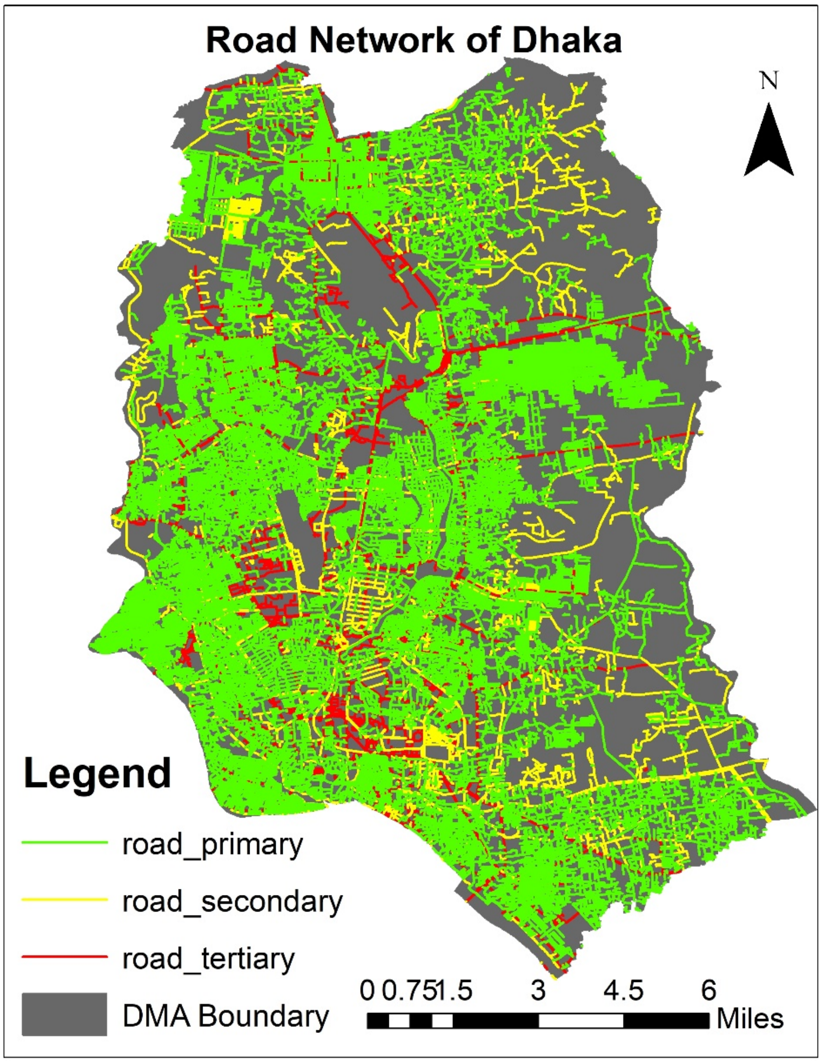


Figure 4.9: Road network of Dhaka

In hierarchy, secondary roads come after the primary roads and tertiary roads are very few in Dhaka.

The map also depicts that, tertiary roads and secondary roads are concentrated mainly in the central part and northern part of the city. Major roads of the city goes through the center of the city from north to south. Except that, few northern and southern part have major portion of secondary and tertiary roads where the built-up density is also lower. The map reveals that, higher density of the city can be attributed as one of the reasons of the city's more primary roads.

Figure 4.10 shows buildings accessibility to the nearest public open space through A) primary, B) secondary and C) tertiary roads. The figures show that most of the buildings within service areas have access to open spaces by primary roads. In Dhaka, total number of buildings are 399658. Among them 58% buildings have natural landscapes within five minutes walking distances through primary, secondary or tertiary roads or through any combination of these roads.

Table 4.3: Buildings accessibility to public open space through road network hierarchy

Buildings within service area through	Number of buildings	Percentage
All roads	233551	58
Primary roads	229168	57
Secondary roads	143625	36
Tertiary roads	107864	27

Table 4.3 also reveals that, among all the buildings, 57% buildings have at least one public open space within five-minute walking distances through primary roads, 36% buildings have this accessibility through secondary roads and 27% buildings must use tertiary roads. Data of the accessibility shows that the total percentage goes beyond 100. This is because there are many buildings those have combination of these three or any two types of road hierarchy. In this study, exclusively primary, secondary and tertiary roads were used to build network dataset. That didn't work as one single road type of Dhaka is not well connected to build network dataset. That reveals that, to go to any public open space almost all buildings must use combination of road types. So, 57% buildings have primary roads accessibility to go to a public open space but in the whole trip, there must be either secondary or tertiary road or both to complete the trip.

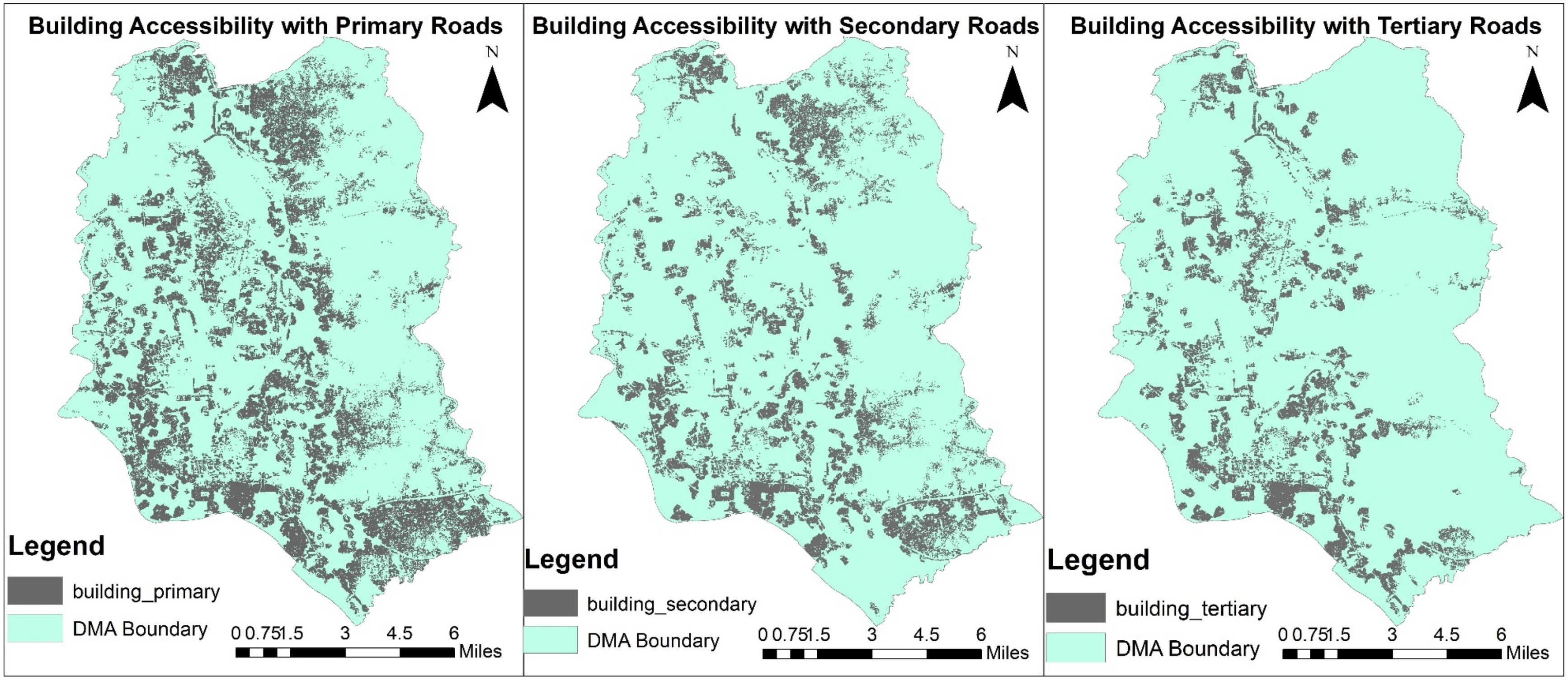


Figure 4.10: Buildings having access to public areas through i) primary roads, ii) secondary roads and iii) tertiary roads.

To measure the correlations between accessibility and demographic characteristics, the spatial distribution of selected demographic data needs to be reviewed. Figure 4.11 shows the correlations between A) Correlations between population density and poor percentage (percentage of poor people), B) Correlations between service areas and population density and C) Correlations between service areas and population density. It shows that, population density and poor percentage of Dhaka has some correlations.

Figure A shows that, in central part, northern part and south-western part, a smaller number of poor people live-in low-density areas. In southern part, which is also the older part of Dhaka, population density is higher and smaller number of poor live in those places. In Dhaka city, location of poor people depends mostly on their income source. Lower density areas are comparatively cheaper and affordable for poor people, but it has less influence over the residence of poor people. Poor people in the city works as day laborers, garments/industry workers, rickshaw pullers and maid servants. Very often they settle in low income areas or in slum areas near high income neighborhoods more profitable for their livelihoods.

Figure B shows Correlations between service areas and population density. It shows that in northern part and some places in the southern part of the city distribution of service areas and population density, both are lower. That may be the results of some planned distribution of public open space. Some places in the central part and southern part of Dhaka, higher amount of public spaces is available for a smaller number of people. That is because of the high living cost of those areas. Rich and higher-middle income people can only live there, so very few people can enjoy more numbers of natural landscapes there.

Figure C shows correlation among service areas distribution and percentage of poor people. Figure shows that, there is eleven significant clusters where 8 is low-low clusters and 3 is high-low clusters. That means, in 8 clusters, places where service areas density is low, percentage of poor is also low. That means that poor people are not the only group to be always deprived of the easy accessibility to natural landscapes. In other 3 clusters, places where service areas density is high, percentage of poor is also low. This correlation proves that, in some places poor people have lower accessibility to natural landscapes. The figure C proves that, poor people don’t live only those areas where population density is higher. As in rich areas, population density is lower, poor people living in those areas can have access to the public spaces in those areas.

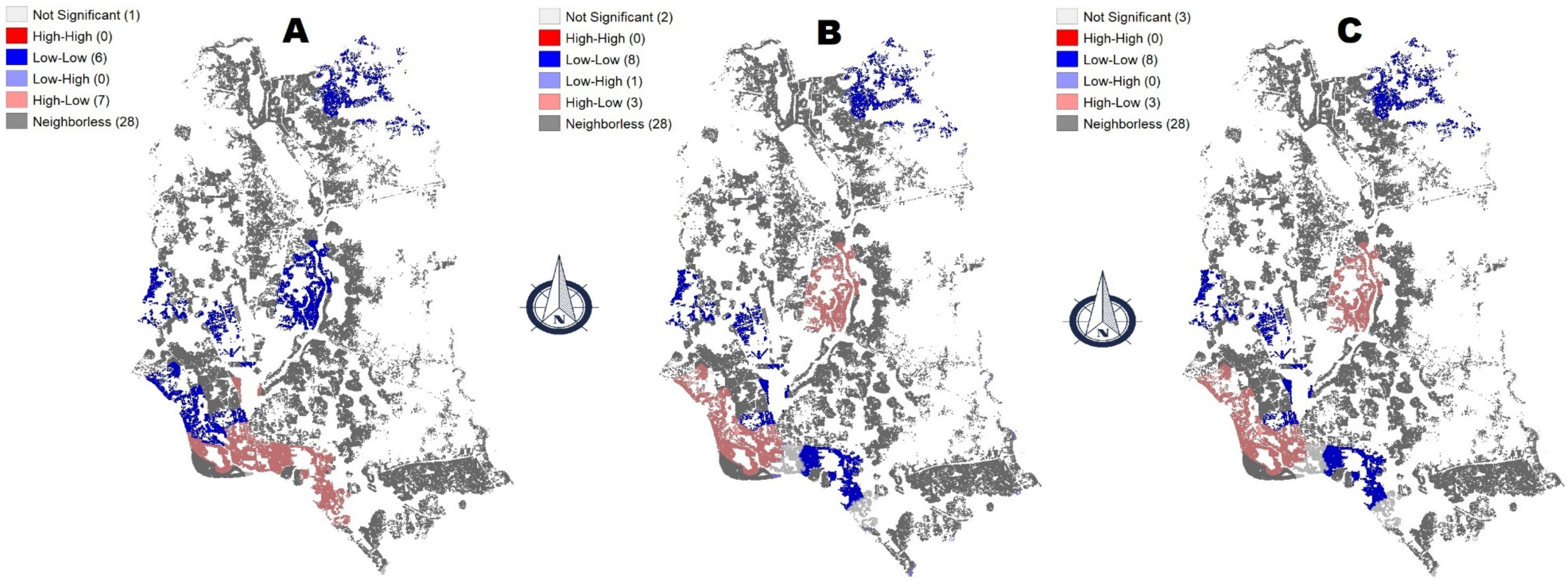


Figure 4.11: A) Correlations between population density and poor percentage, B) Correlations between service areas and population density and C) Correlations between service areas and population density

4.5.2 Kolkata

4.5.2.1 Correlation Analysis Between Landscapes and Air Pollution

PM 10 pollution and NDVI:

PM 10 pollution of Dhaka and NDVI of Kolkata is negatively correlated. Figure 4.13 represents the PM 10 pollution map and NDVI map of Kolkata for the year 2018. The map shows that, air pollution is higher mainly in the central places of Kolkata where the density of built-up areas is higher. NDVI values in those places are also negative. On eastern and south-eastern part of Kolkata, NDVI value is lower and negative, but pollution on those areas is comparatively lower.

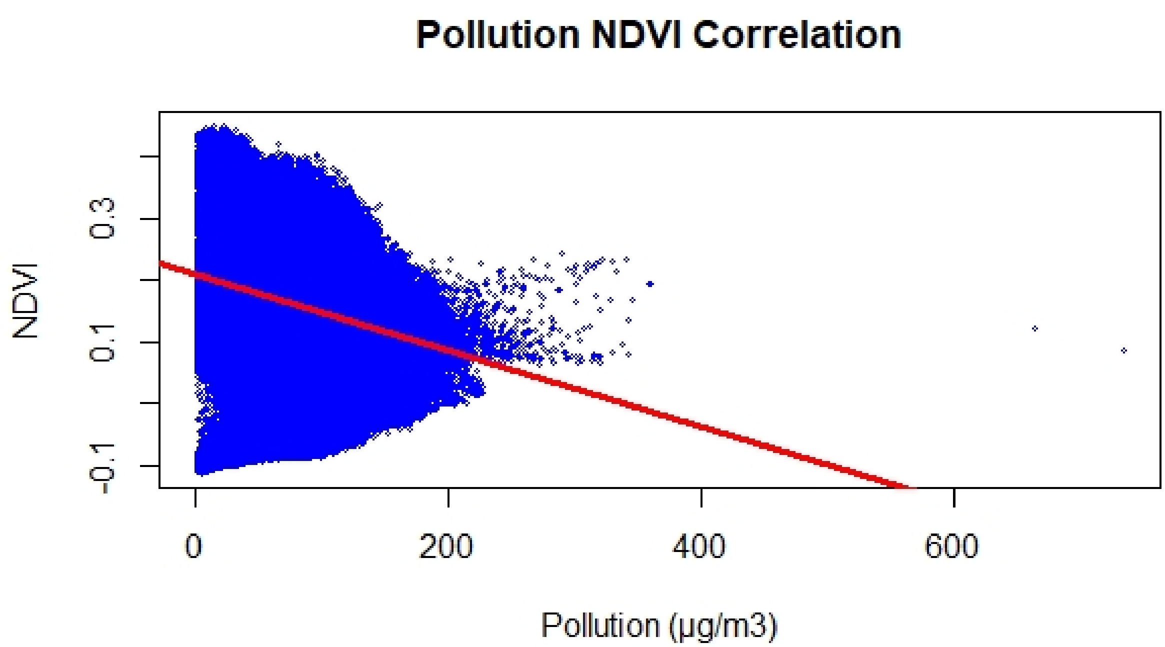


Figure 4.12: Correlation between PM 10 pollution and NDVI for Kolkata in 2018

Kolkata has lots of crop land and barren land which increases air pollution. Left over crop land also act as barren land. They can increase pollutant by burning. (Wu et al. 2015). Negative correlations between NDVI and PM 10 pollution of Kolkata in 2018 is shown in figure 4.12. The R^2 value of this correlation is **-0.28** that means that, 28% variations of pollution are explained by NDVI values. So, insignificantly, where the pollution is higher, NDVI values are lower.

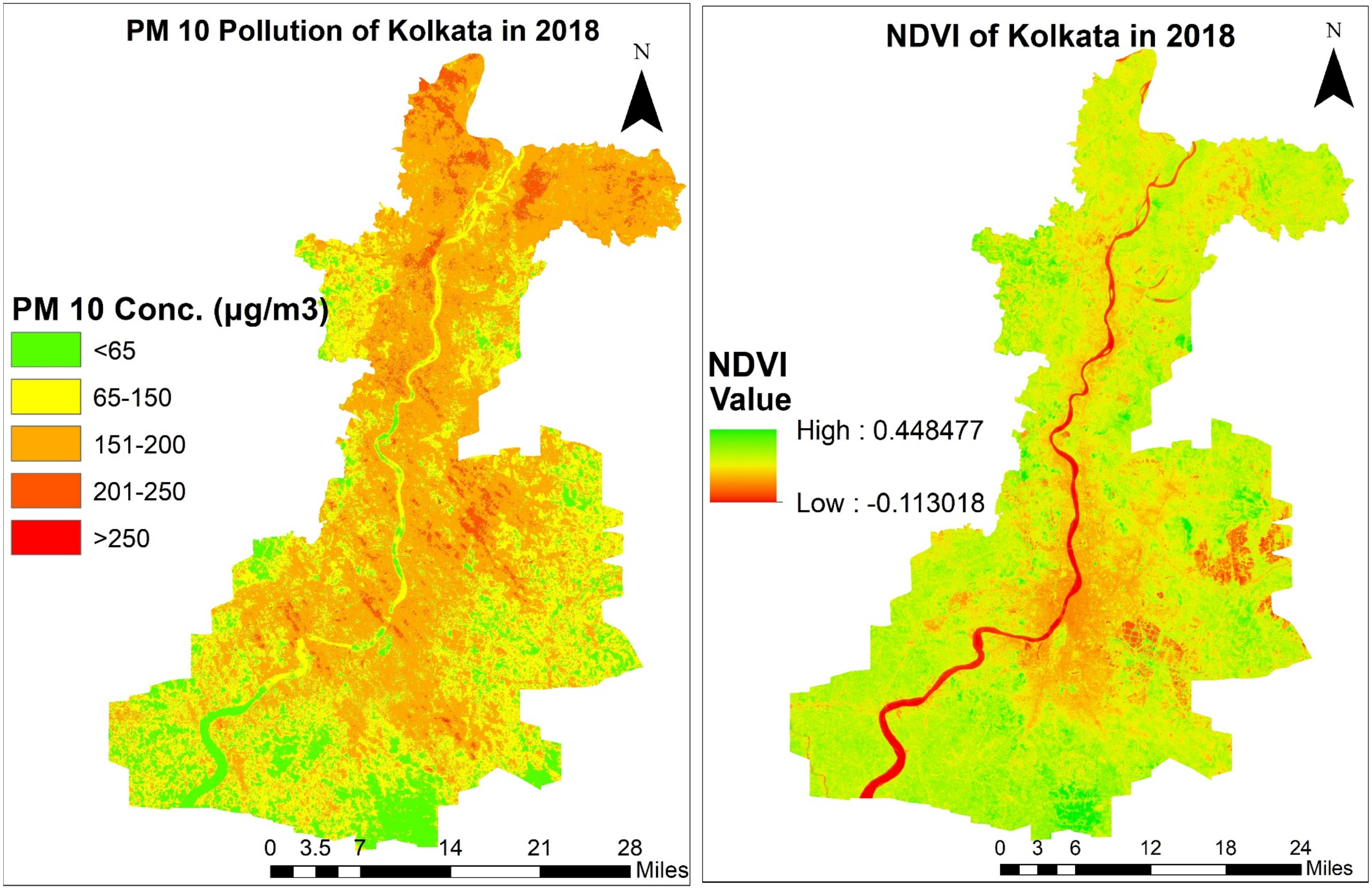


Figure 4.13: PM 10 pollution and NDVI map of Kolkata in 2018

PM 10 Pollution and NDBI:

PM 10 pollution and NDBI values of Kolkata are also highly correlated. Figure 4.15 shows that, NDBI values are lower in north-eastern and north-western part of Kolkata which areas have have higher pollution rate. Central part of Kolkata has higher pollution rate and NDBI values as well. One small part in north western part of Kolkata has also negative and lower value which also matches the lower pollution rate geographically. Areas along both side of the river of the city has higher NDBI values as these places have high-density built-up areas and barren lands which are source of pollution. PM 10 pollution rate is also higher in these areas.

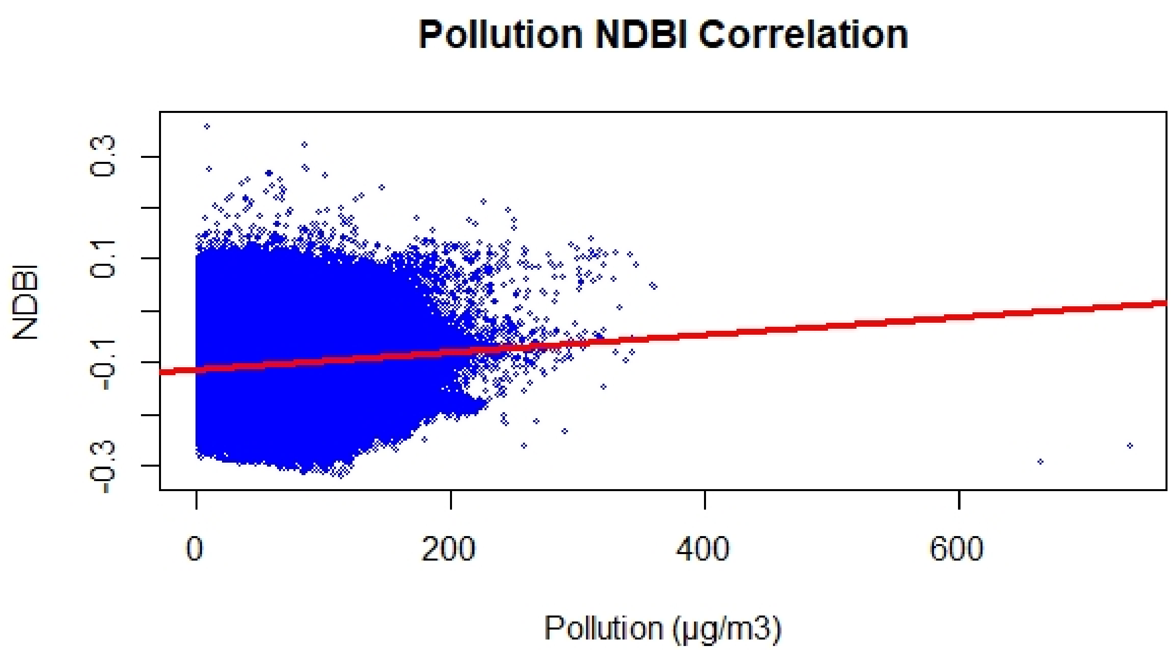


Figure 4.14: Correlation between PM 10 pollution and NDBI for Kolkata in 2018

Positive correlations between NDVI and PM 10 pollution of Kolkata in 2018 is shown in figure 4.14. The distribution of data and trendline shows that, these values have insignificant but a positive correlation which means, where pollution is higher, NDBI values are also higher. The R^2 value of this correlation is **+0.1** that means that, only 10% variations of pollution are explained by NDBI values.

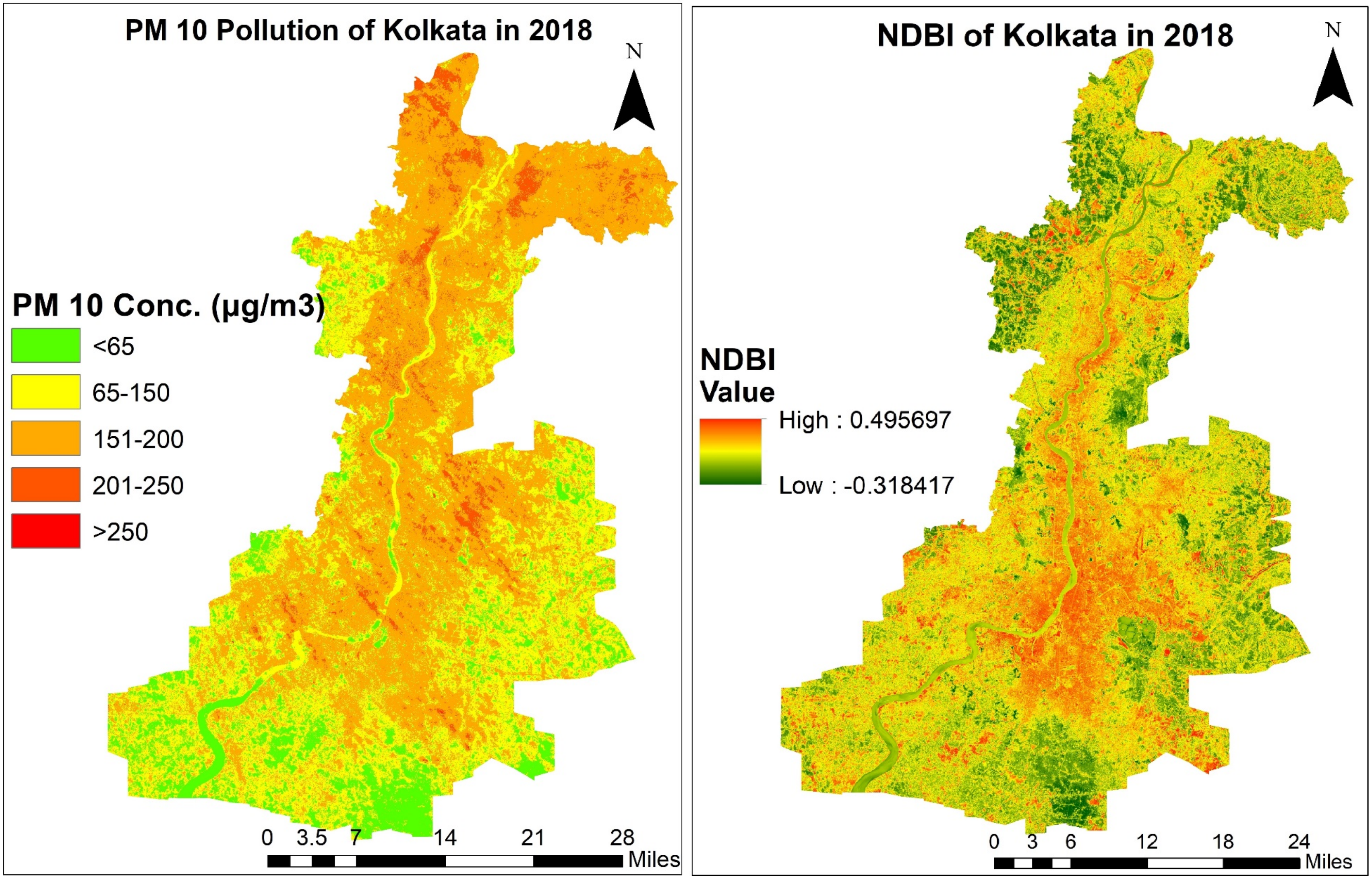


Figure 4.15: PM 10 pollution and NDBI map of Kolkata in 2018

PM 10 Pollution and NDWI:

PM 10 pollution and NDWI has also insignificant relations. Figure 4.17 represents the PM 10 pollution map and NDWI map of Kolkata for the year 2018. The map shows that, air pollution is higher mainly in the central places of Kolkata where the density of built up areas are also higher. NDWI values in those places are also negative. On northern part of Kolkata, NDWI value is higher and positive, but pollution on northern part is higher and southern part is comparatively lower. Though NDWI value of Kolkata don't have a high significance, still NDWI value has negative correlation with PM 10 pollution.

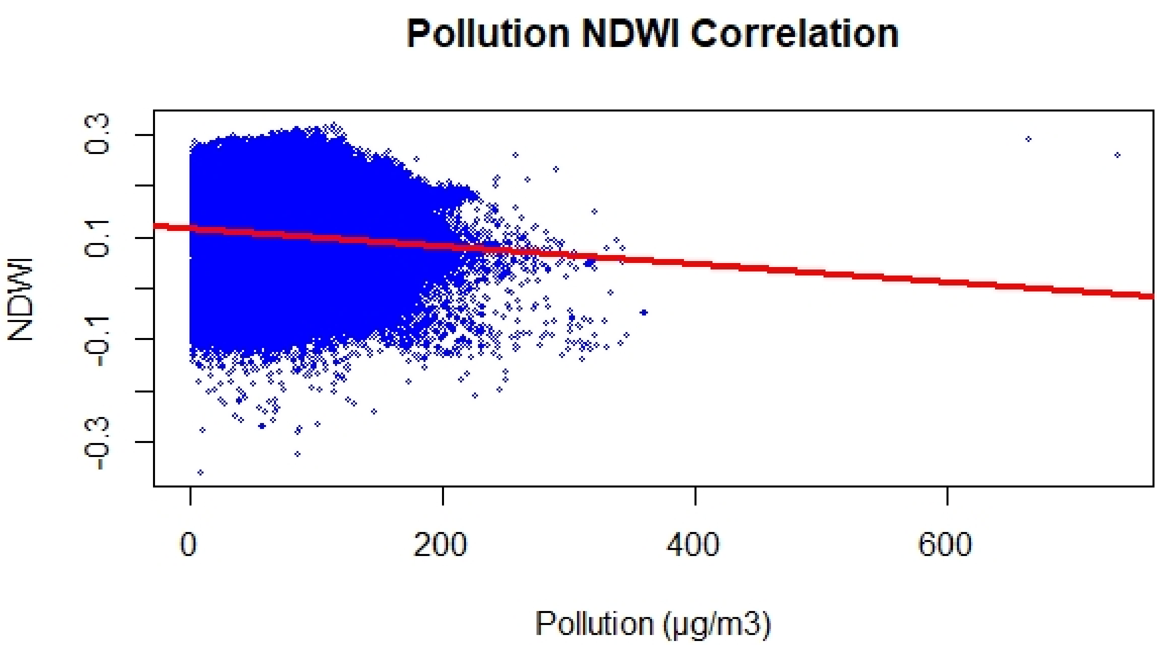


Figure 4.16: Correlation between PM 10 pollution and NDWI for Kolkata in 2018

Negative correlations between NDWI and PM 10 pollution of Kolkata in 2018 is shown in figure 4.16. The distribution of data and trendline shows that, these values have a negative correlation which means, where pollution is higher, NDWI values are lower. The R^2 value of this correlation is -0.1 that means that, only 10% variations of pollution are explained by NDWI value.

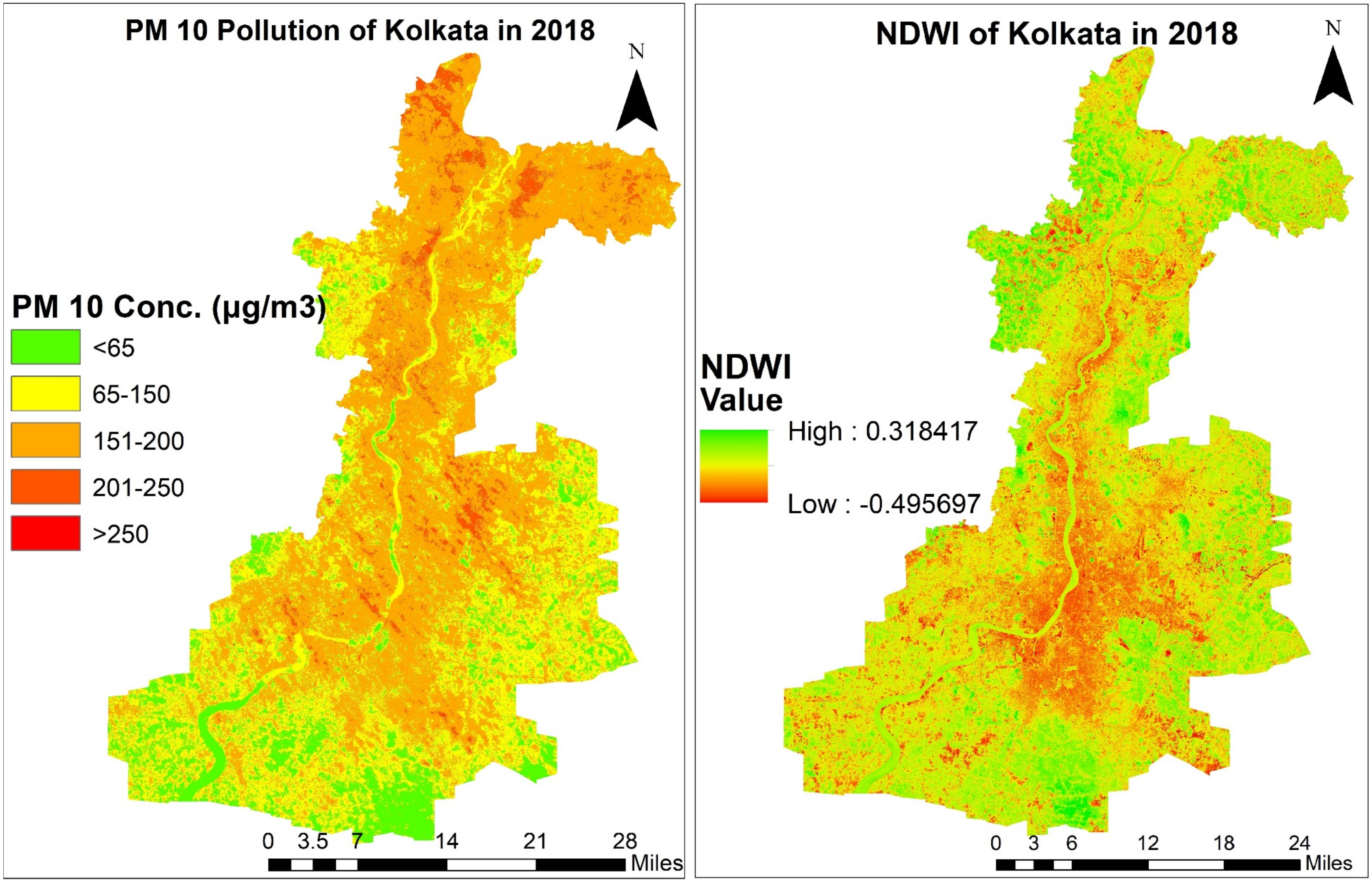


Figure 4.17: PM 10 pollution and NDWI map of Kolkata in 2018

4.5.2.2 Measurement of Accessibility to Public Open Space

Service area:

Figure 4.7 shows the service areas of the natural landscapes of Kolkata. The service areas covered almost 26% areas of Kolkata city. The figure represents that, service area of all green spaces and waterbodies are distributed in mainly central part of the city and along the river Hooghly.

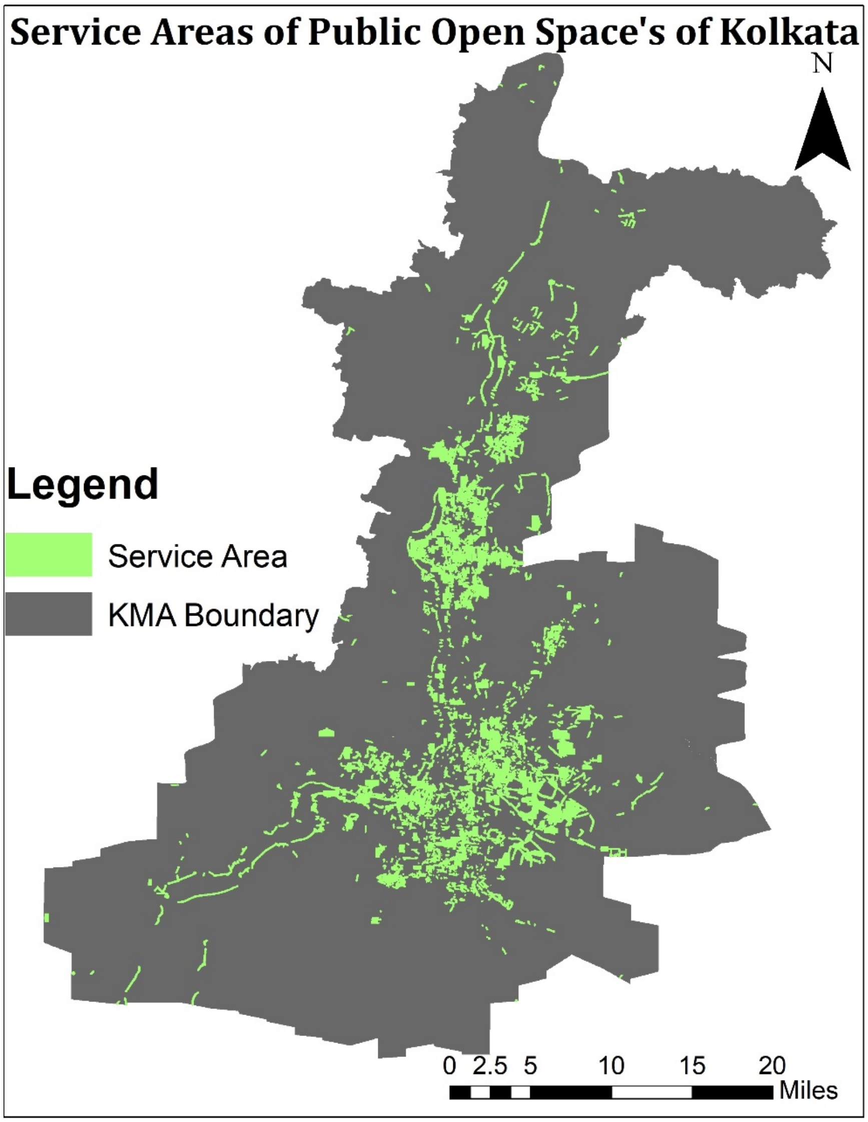


Figure 4.18: Service area of natural landscapes

In this study, same as the Dhaka study, green spaces and waterbodies have taken from OSM data which are not real time data. These areas are not officially recognized as natural landscapes by the government rather all the green spaces and waterbodies have taken into consideration in this study.

There may be some green areas and waterbodies which are not functioning well, or which is restricted for common people to go. In those cases, service areas of some natural landscapes may sometimes represent wrong ideas.

Figure 4.19 represents the road networks of Kolkata. It shows that, in Kolkata the share of primary roads is significantly higher than secondary and tertiary roads. This can be one reason of 26% areas of the city under service areas.

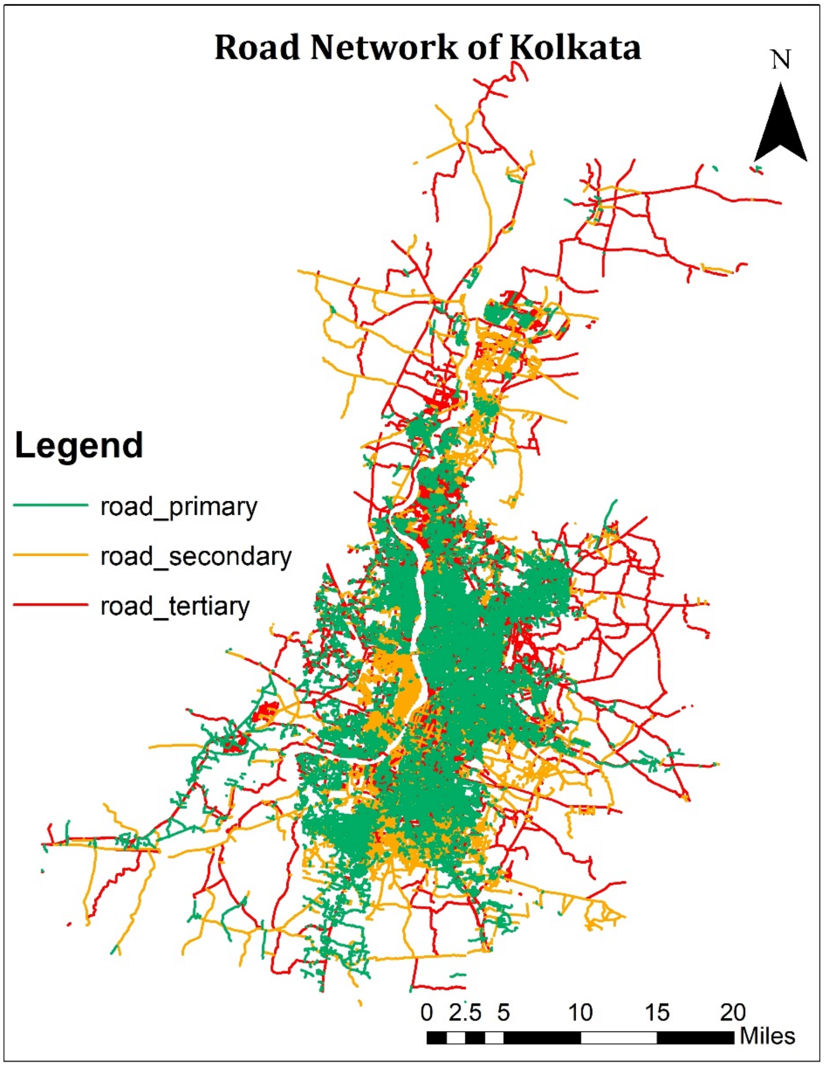


Figure 4.19: Road network of Kolkata

In hierarchy, secondary roads come after the primary roads and tertiary roads are very few in Kolkata.

The map also depicts that, tertiary roads and secondary roads are concentrated mainly in central part and northern part of the city. Major road of the city goes through the center of the city from north to south. Kolkata is regarded as a hub of districts neighboring it. So, major roads also go through all direction from center of Kolkata. Except that, few northern and southern part have major portion of secondary and tertiary roads where the built-up density is also lower. The map reveals that, higher density areas of the city have major portions of primary roads.

Figure 4.20 shows buildings accessibility to the nearest public open space through A) primary, B) secondary and C) tertiary roads. The figures show that very few of the buildings within service areas have access to open spaces through primary roads. In Kolkata, total number of buildings are 578378. Among them 25% buildings have natural landscapes within five minutes walking distances through primary, secondary or tertiary roads or through any combination of these roads.

Table 4.4: Buildings accessibility to public open space through road network hierarchy

Buildings within service area through	Number of buildings	Percentage
All roads	145976	25
Primary roads	61939	11
Secondary roads	12143	2
Tertiary roads	41879	7

Table 4.4 also reveals that, among all the buildings, only 11% buildings have at least one public open space within five-minute walking distances through primary roads, 2% buildings have this accessibility through secondary roads and 7% buildings must use tertiary roads. There are many buildings those have combination of these three or any two types of road hierarchy. In this study, exclusively primary, secondary and tertiary roads were not used to build network dataset. The reason behind that is one single road type of Kolkata is not well connected to build network dataset. That reveals that, to go to any public open space almost all buildings must use combination of road types. So, 11% buildings have primary roads accessibility to go to a public open space but in the whole trip, there must be either secondary or tertiary road or both to complete the trip.

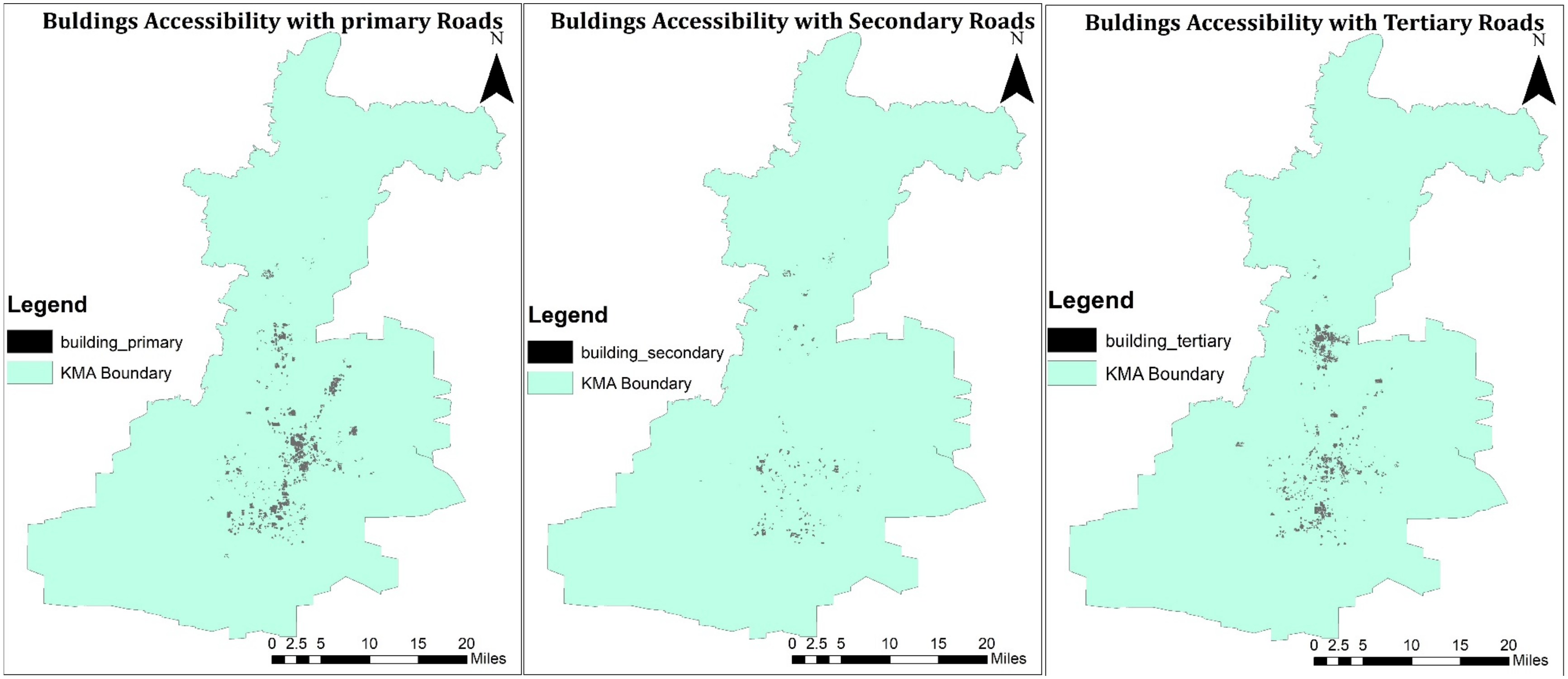


Figure 4.20: Buildings having access to public areas through i) primary roads, ii) secondary roads and iii) tertiary roads.

Green and natural landscapes are an important part of city life for giving people relief from the monotony and stress of city life. It is also important for healthy environment of the city. it is necessary to have these spaces within walking distances from every people's houses. The study revealed the inaccessibility of the available public spaces of Dhaka and Kolkata and their spatial dependence on people's demographic characteristics. The distribution of these spaces should be distributed according to population density ensuring every person's efficient accessibility to it.

CHAPTER 5: SIGNIFICANCE OF THE RESEARCH AND CONCLUSION

5.1 Significance of the research

This study analyzed historical urban growth, land cover classification, impact of land cover change on pollution, and impact of pollution on people's accessibility to urban natural landscapes of Dhaka and Kolkata. Dhaka and Kolkata are two cities of two neighboring countries Bangladesh and India respectively, sharing same language, similar physical geography, culture and demographic characteristics. Analyzing these two cities from same point of research is the highlight of this research.

This study has performed land cover classification of the two study areas using Google Earth Engine (GEE). Using the GEE platform gave the researcher the opportunity to work with all the images of a selected year simultaneously and work with six landcovers types. It helped to distinguish each landcovers from the other more efficiently comparing their change of reflectance over several seasons. This method also revealed the pattern of land cover change in these two cities from the analysis. The reasons behind the land cover change and different changing pattern of geographically and demographically similar cities have also addressed in this research.

In the second part of the research, impacts of land cover change have been reviewed. Among the impacts, impact of Particulate Pollution (PM 2.5 and PM 10), one of the least acknowledged impacts in South Asia have been analyzed.

In south Asia, regular pollution measurement methods using ground stations are less popular due to cost incurred and maintenance challenge. So, method to measure pollution using satellite images and few ground stations have been used in this research. The changes of pollution in two different years for both the cities have been done which describes the change and geographical extent of change of particulate pollution over the years. Due to recent air pollution severity in south Asian cities, air pollution mapping integrating satellite images has become an emergence (Brauer et al. 2019). This study also complements the necessity of pollution mapping of the cities having insignificant amount of ground stations and shorthanded maintenance and monitoring system.

In the third part of the research, accessibility to natural landscapes by the city dwellers have been figured out after analyzing the impacts of pollution over the environment and people. The particulate pollution has expanded all over the cities. The areas of lower pollution have been found out. The accessibility to the lower pollution areas have been measured using network analysis method. Accessibility was divided into three types based on road hierarchy. Three types of accessibility show availability of low pollution areas for people to go to take a fresh breath, have recreation and a health environment. Hierarchy of accessibility shows degree of complexity that people must endure to go to those places. It also explains the distribution of those places using the actual trip length. It also analyzed the influence of demographic characteristics over the establishment and distribution of these natural landscapes. It also discussed about the correlations of the distribution of these places with people's socio-economic characteristics for cross-checking the spatial equity in the distribution.

5.2 Conclusion

Due to high population density followed by high land value in South Asia, land covers are changing in a dramatic manner. Land cover of Dhaka have been changing since it was declared the capital city for the newborn nation Bangladesh in 1971. Kolkata has been experiencing change since division of Indian subcontinent in 1947. Both, Dhaka and Kolkata have massive demand on land resulting from increasing population. The cities have experienced change inf landcovers gradually over the last few decades.

In Dhaka, landcovers like built up area and barren land have increased in a significant amount. At the same time, few landcovers changes in a transitory basis over the years like waterbody to wetland, wetland to vegetation, vegetation to barren land and agricultural to barren land with the change of seasons. Though these conversions are interim, these conversions work as a step to the ultimate conversion of any land cover to build up area.

In Kolkata, built up areas and barren lands have increased but no significant pattern was found. Kolkata has grown on both side of Hooghly river. Concentration of built up areas and barren lands also expanded on both side of Hooghly river considering KMC as the center. Suburban areas of Kolkata, specially the western and eastern part had many agricultural lands which is transforming at a rapid rate.

Land cover change detection using multi seasonal images makes it convenient to distinguish the variations which have close range pixels and overlap with one another throughout the year. A thorough visual analysis also revealed the unique patterns of landcover change (Oliphant et al. 2019). The pattern reveals how the land covers of the cities has been changing so far gradually and more strategically. This strategic land cover change is responsible for the loss of waterbody, vegetation and other natural landscapes of the city. Most often, these land covers change seems natural and draw no attention to the policy makers or conservationist of natural landscapes. This multi-seasonal image analysis using Google Earth Engine can identify these alterations work as the foundation of dynamic land cover policy.

Air pollution increase is one of the inevitable impacts of landcover change (Brauer et al. 2019). Land cover change acts as a catalyst to increase the source of pollution. The study found a significant correlation between land cover change and the increase of pollutant sources like impervious spaces, roads followed by increasing vehicles, industrialization and commercialization at a large scale. the pollution maps from satellite images showed the change of pollution and extent in these two cities in a different pattern but in a similar increasing direction.

Both in Dhaka and Kolkata, in 2014, particulate matter concentration was concentrated in the center of the city in a higher degree. In 2018, though the extent of pollution decreased in a smaller amount at the center of the cities, it expanded in greater areas.

In Dhaka, particulate matter pollution is highly correlated with landcovers where NDVI and NDWI values are negatively correlated to particulate pollution and NDBI value is positively correlated.

In Kolkata, landcovers correlations to pollution exists but not in a significant manner. Kolkata city is mainly centered within KMC. Kolkata has more agricultural areas on western and eastern side of Hooghly river. Agricultural areas produce more pollution than waterbodies and green spaces covered with trees and grass (Wu et al. 2015). This can be the reason for insignificant correlation between NDVI values and pollution of Kolkata.

Accessibility to green and other natural landscapes is always a basic need for people to live a healthy life. Increasing pollution is highly correlates to the loss of natural landscapes. On the other hand, increasing pollution has made natural places an emerging need to the city dwellers. With time, these places are disappearing from the neighborhoods and accessibility to the remaining natural environment are becoming difficult. Again, these places are not distributed maintaining social justice and spatial equity rather influenced by socio-economic characteristics of the residents of several neighborhoods.

In Dhaka, service areas of natural landscapes are more accessible to people than Kolkata. Dhaka's natural landscapes are inadequate but distributed all through the cities. Though Dhaka has better accessibility, most often the accessibilities are not provided using only local or primary roads. Though service areas are within walkable distance, people need to use secondary and even tertiary roads to go to those places.

In Kolkata, service areas are very few. In Kolkata, residential areas are concentrated at the center, along with the Hooghly river. The service areas of natural landscapes are concentrated mostly on the south-western part of the city. Due to the distribution and lack of public natural landscapes, people of Kolkata have lower accessibility to public natural landscapes.

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APPENDIX

```
Kolkata 2007-08                Get Link   Save   Run   Reset   Apps

Imports (13 entries)
  var roi: Polygon, 20 vertices
  var Waterbody: FeatureCollection (55 elements)
  var Wetland: FeatureCollection (30 elements)
  var Vegetation: FeatureCollection (84 elements)
  var Agricultural: FeatureCollection (67 elements)
  var Builtup: FeatureCollection (52 elements)
  var BarrenLand: FeatureCollection (33 elements)
  var VWaterbody: FeatureCollection (15 elements)
  var VWetland: FeatureCollection (10 elements)
  var VVegetation: FeatureCollection (15 elements)
  var VAgricultural: FeatureCollection (14 elements)
  var VBuiltup: FeatureCollection (14 elements)
  var VBarrenLand: FeatureCollection (17 elements)
var maskL8 = function(image_m) {
  var qa = image_m.select('BQA');
  var mask = qa.bitwiseAnd(1 << 4).eq(0);
  return image_m.updateMask(mask);
};

var image_m = ee.Image(ee.ImageCollection('LANDSAT/LT05/C01/T1_TOA')
.filterBounds(roi)
.filterDate('2008-06-16', '2008-10-15')
.map(maskL8)
.median());
Map.addLayer(image_m, {bands: ['B4', 'B3', 'B2'], max: 0.3}, 'image_m');

var maskL8 = function(image_s) {
  var qa = image_s.select('BQA');
  var mask = qa.bitwiseAnd(1 << 4).eq(0);
  return image_s.updateMask(mask);
};

var image_s = ee.Image(ee.ImageCollection('LANDSAT/LT05/C01/T1_TOA')
```

Figure 1: Land cover classification code

```
.map(maskL8)
.median());
Map.addLayer(image_s, {bands: ['B4', 'B3', 'B2'], max: 0.3}, 'image_s');

var maskL8 = function(image_w) {
  var qa = image_w.select('BQA');
  var mask = qa.bitwiseAnd(1 << 4).eq(0);
  return image_w.updateMask(mask);
};

var image_w = ee.Image(ee.ImageCollection('LANDSAT/LT05/C01/T1_TOA')
.filterBounds(roi)
.filterDate('2007-10-16', '2008-03-15')
.map(maskL8)
.median());
Map.addLayer(image_w, {bands: ['B4', 'B3', 'B2'], max: 0.3}, 'image_w');


var mergedCollection = image_s.addBands(image_w);
print('mergedCollection: ', mergedCollection);
Map.addLayer(mergedCollection, {bands: ['B4', 'B3', 'B2'], max: 0.3}, 'mergedCollectic

//merge
var newfc = Waterbody.merge(Wetland).merge(Vegetation).merge(Agricultural).merge(Built
print(newfc);

//create training data
var bands = ['B2', 'B3', 'B4', 'B5', 'B6', 'B7'];
var training = mergedCollection.select(bands).sampleRegions({
  collection: newfc,
  properties: ['landcover'],
  scale: 30
  });
print(training);

//Train the classifier
var classifier = ee.Classifier.cart().train({
```

Figure 2: Land cover classification code

Kolkata 2007-08 Get Link Save Run Reset Apps

```
//Train the classifier
var classifier = ee.Classifier.cart().train({
  features: training,
  classProperty: 'landcover',
  inputProperties: bands
  });

//Run the classification
var classified = mergedCollection.select(bands).classify(classifier);

//Display classification
Map.centerObject(newfc, 11);
Map.addLayer(mergedCollection,
{bands: ['B4', 'B3', 'B2'], max: 0.3},
'Landsat image');
Map.addLayer(classified,
{min: 1, max: 6, palette: ['3336FF', '62F5FA', '2B802D', '99F986', 'F1510C', 'FDF9A2']
'classification');
Map.addLayer(newfc)

// Export the image, specifying scale and region.
Export.image.toDrive({
  image: classified,
  description: 'imageToDriveExample',
  scale: 30,
  region: roi
});

//Merge into one FeatureCollection
var valNames = VWaterbody.merge(VWetland).merge(VVegetation).merge(VAgricultural).merg

var validation = classified.sampleRegions({
  collection: valNames,
  properties: ['landcover'],
  scale: 30,
});
```

Figure 3: Land cover classification code

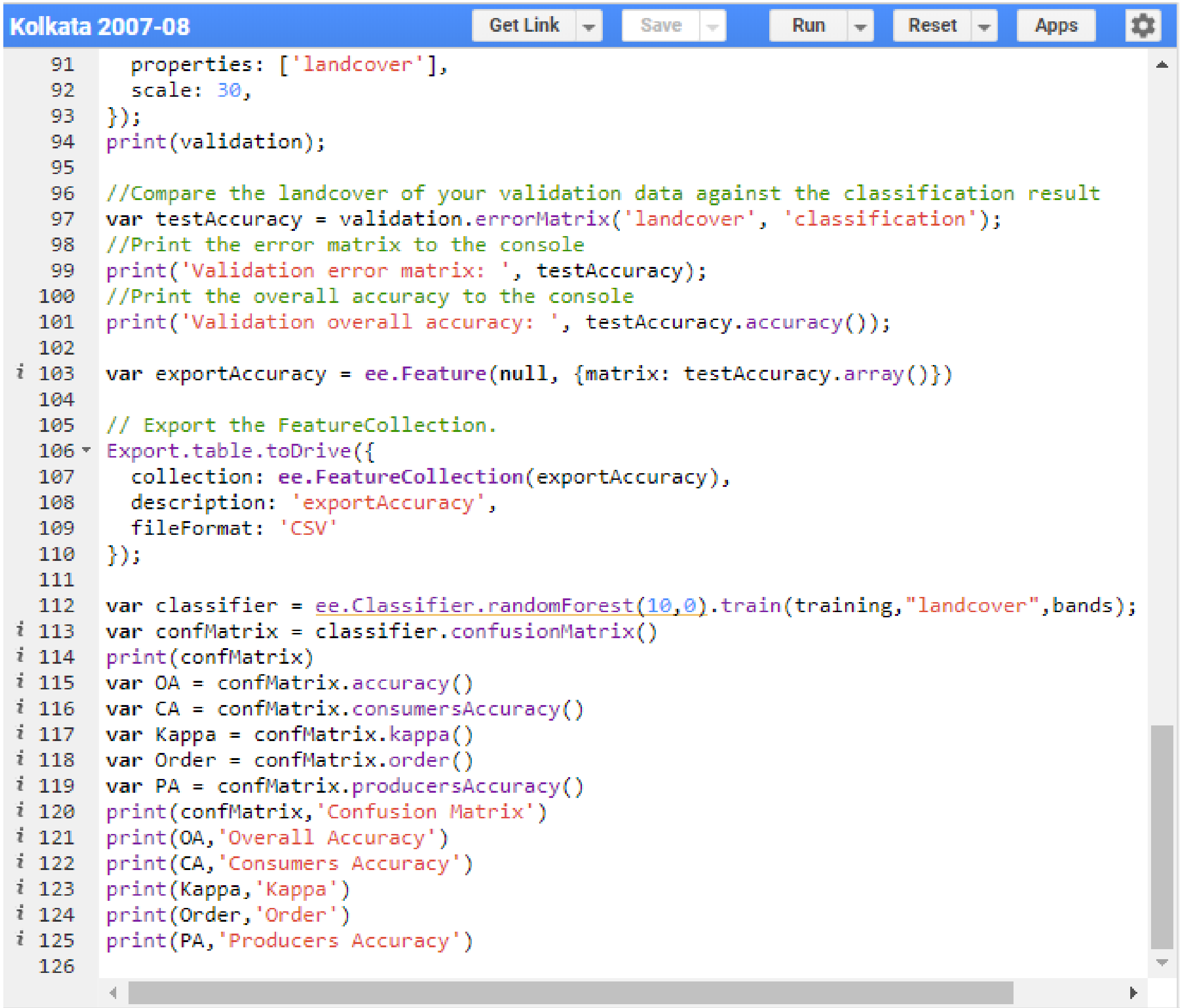

Figure 4: Land cover classification code

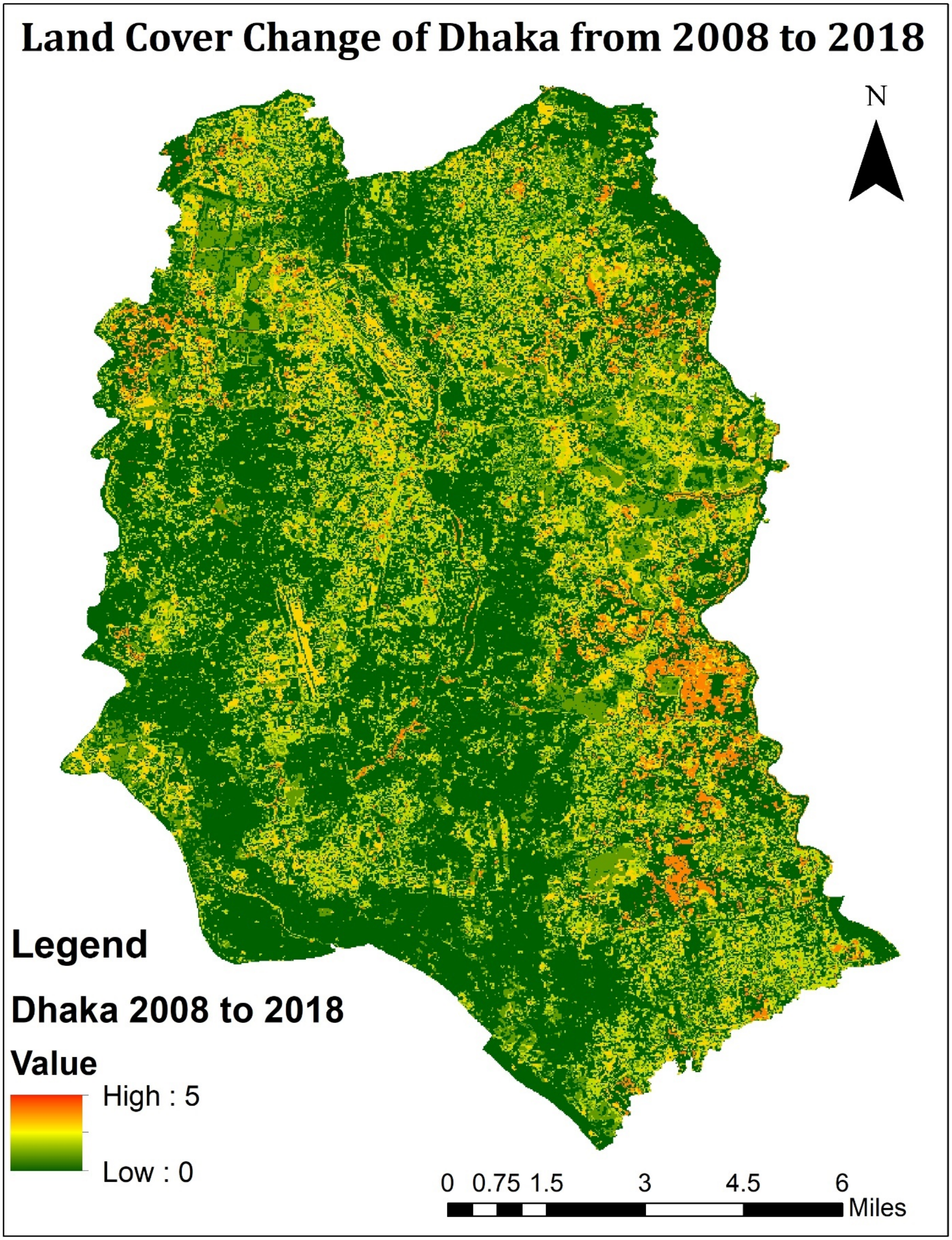

Figure 5: Change detection of Dhaka Land cover from 2008 to 2018

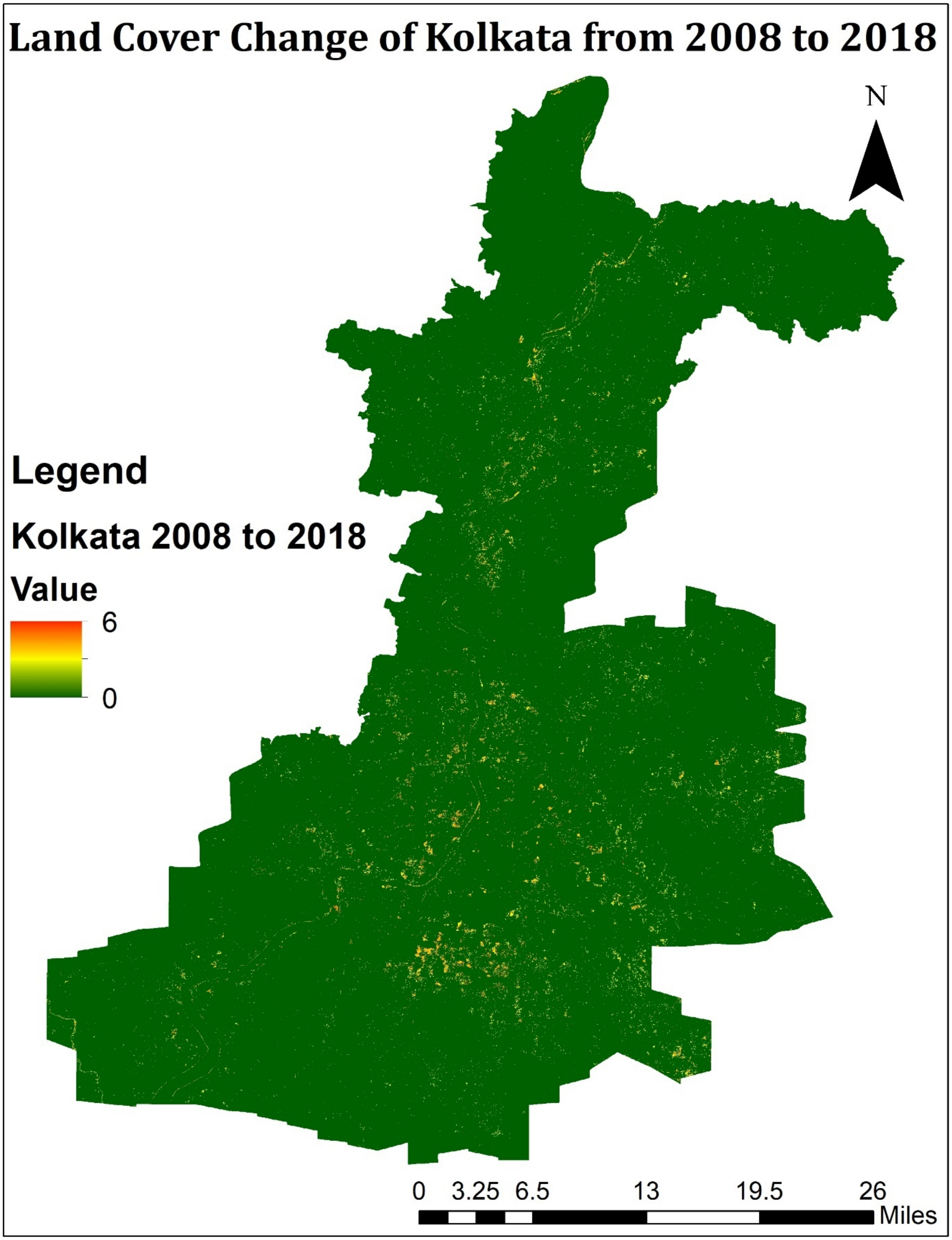

Figure 6: Change detection of Kolkata landcover from 2008 to 2018

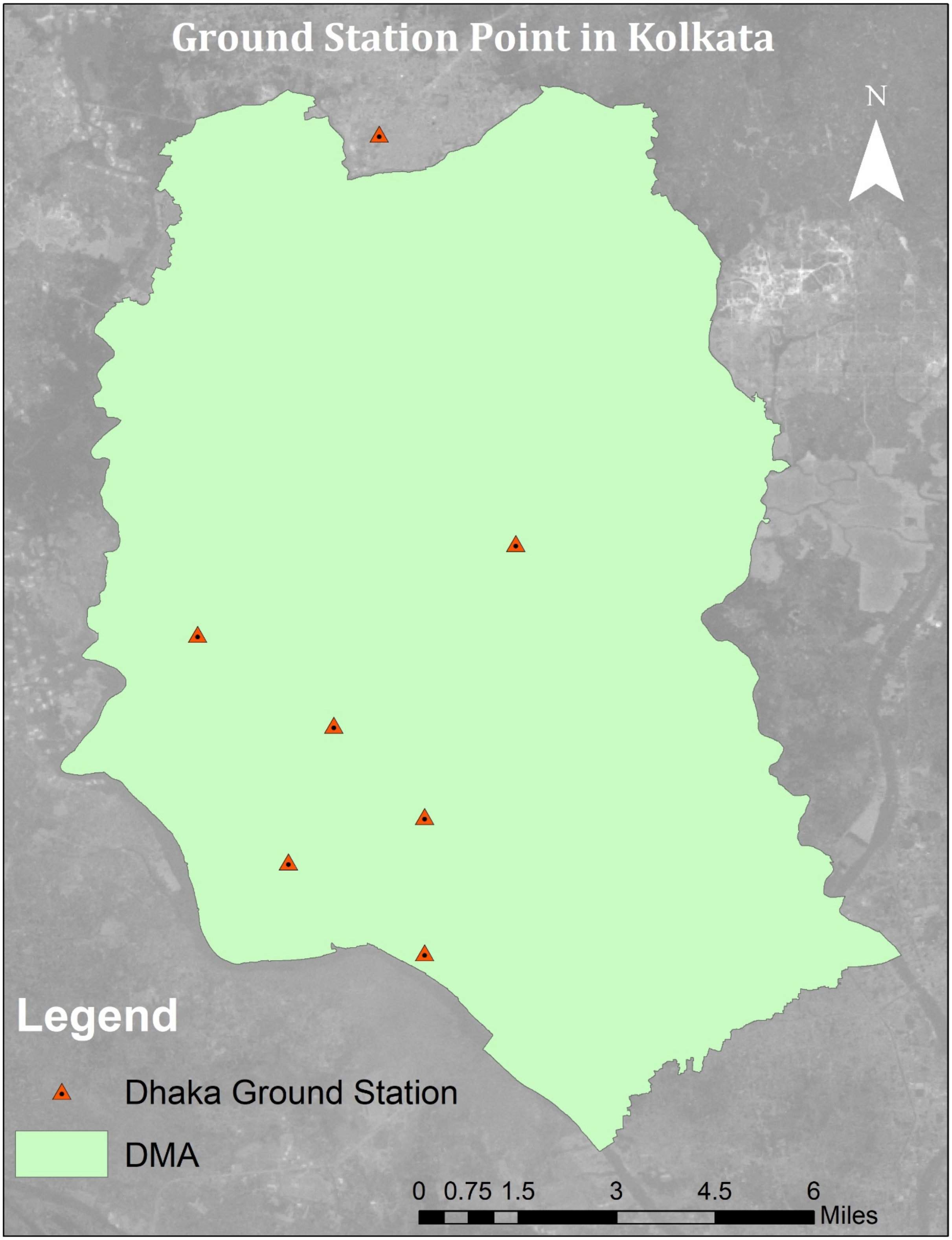

Figure 7: Ground station for pollution measurement of Dhaka

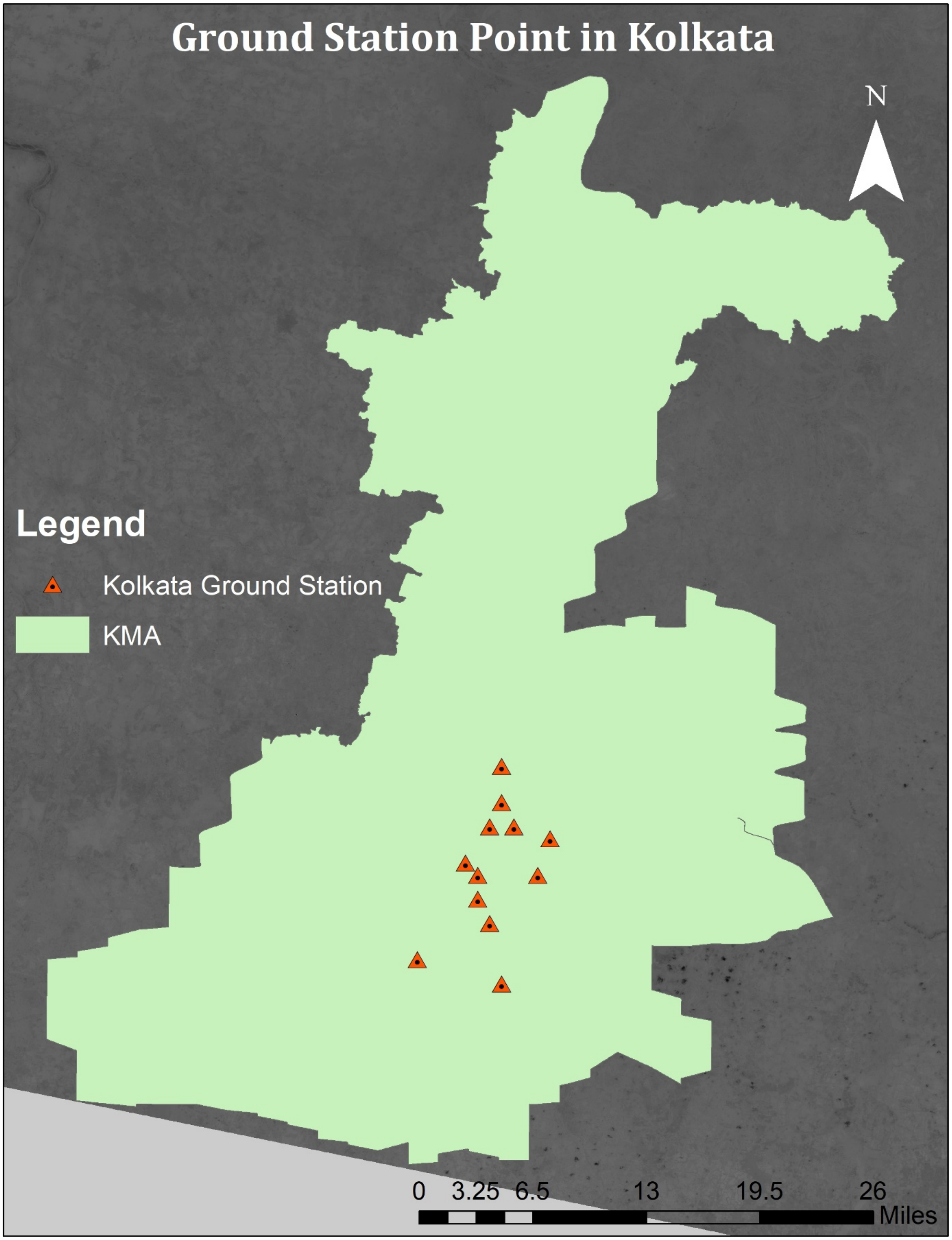

Figure 8: Ground station for pollution measurement of Kolkata

Console | Terminal | Jobs

~/

```
> > setwd("J:/Solaiman/Dhaka")
  > dhaka <- read.table("pol_ndwi2.txt",header = T)
  >
      >  View(dhaka)
  > > library(dplyr)

  Attaching package: ‘dplyr’

  The following objects are masked from ‘package:stats’:

      filter, lag

  The following objects are masked from ‘package:base’:

      intersect, setdiff, setequal, union

  > fndwi2<-filter(dhaka, B2>=-1, B2<=1)
  > View(fndwi2)
  > cor(fndwi2$B1, fndwi2$B2)
  [1] -0.8753332
  > fndwi2Reg <- lm(fndwi2$B2~fndwi2$B1)
  >
      > summary(fndwi2Reg)

  Call:
      lm(formula = fndwi2$B2 ~ fndwi2$B1)

  Residuals:
      Min        1Q    Median        3Q       Max
  -0.34162 -0.01586  0.00044   0.01667   0.30153

  Coefficients:
```

Figure 9: R code for non-spatial correlation

```
Console   Terminal ×   Jobs ×
~/
[1] -0.8753332
> fndwi2Reg <- lm(fndwi2$B2~fndwi2$B1)
>
    > summary(fndwi2Reg)

Call:
    lm(formula = fndwi2$B2 ~ fndwi2$B1)

Residuals:
    Min       1Q   Median       3Q      Max
-0.34162 -0.01586  0.00044  0.01667  0.30153

Coefficients:
    Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.505e-01  3.896e-04    1156   <2e-16 ***
    fndwi2$B1   -2.314e-03  2.197e-06   -1053   <2e-16 ***
    ---
    Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02728 on 338632 degrees of freedom
Multiple R-squared:  0.7662,    Adjusted R-squared:  0.7662
F-statistic: 1.11e+06 on 1 and 338632 DF,  p-value: < 2.2e-16

> plot(fndwi2$B2, fndwi2$B1, col="blue", pch=1, cex=0.4,
      +       main= "Pollution NDWI Correlation",
      +       xlab="NDWI", ylab="Pollution (µg/m3)")
>
    > abline(fndwi2Reg, lty=1, lwd=3, col="red")
Error in abline(fndwiReg, lty = 1, lwd = 3, col = "red") :
    object 'fndwiReg' not found
> abline(fndwi2Reg, lty=1, lwd=3, col="red")
```

Figure 10: R code for non-spatial correlation