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Dhaka city, Bangladesh**

(バングラデシュのダッカ市における持続可能な都市
開発のための都市化動態と生態系サービスの地理空
間分析)

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Abstract

Urbanization is one of the most significant social transformations of the contemporary era. In the 21st century, urban areas, including Dhaka, are increasingly facing challenges from natural and human-induced crises, such as flooding, air pollution, and the urban heat island effect. Urbanization dynamics and ecosystem service assessment are essential to enhance urban resilience against these threats. The relationship between ecosystem services (ES) and urbanization is crucial for sustainable development. Rapid urbanization threatens Dhaka city's natural capital, affecting ES's delivery through changes in land use and land cover (LULC). This study categorized LULC classes and functions from 2000-2021 using the Common International Classification of Ecosystem Services (CICES) framework, utilizing multitemporal satellite images and spectral signature-based indices. Five major LULC types were identified: waterbodies, vegetation cover, built-up areas, agricultural land, and bare land. The findings revealed a 94% increase in built-up areas and a 70% decrease in water bodies. Bare land initially increased until 2018 but later decreased due to conversion to built-up areas. Agricultural land decreased by 60%, particularly in rural-urban fringe areas, with bare land experiencing the highest conversion at 48.94% of its total area. From 2000 to 2021, 16.80% of agricultural land, 21.64% of vegetation cover, and 12.63% of waterbodies were converted to built-up areas.

Ecosystem services refer to the benefits humans obtain from these LULC classes, categorized into provisioning, regulating, supporting, and cultural services. When these services are quantified in monetary terms, they are called ecosystem service values. ESV was globally aligned and adjusted with regional correction factors, developing region-specific coefficients for the study area. Using GIS zonal statistics, the study calculated region-wise mean ESV, finding the highest mean value in the rural-urban fringe area in 2000 (36.12%) and the lowest in the NI area (11.29%). Over the study period, ESV significantly decreased, particularly in the rural-urban fringe area (-87.95%) and other urban zones. Conversion of waterbodies resulted in an ESV loss of \$273 million. ESV losses were observed across all ES types: provisioning (-71.59%), regulating (-69.44%), and cultural services (-62.45%), increasing the city's vulnerability to flooding, waste

assimilation, and pollution. The research also examined the trade-offs between the ecosystem service bundles (provisioning, regulating, and cultural). The most synergistic relationship between provisioning and regulating ES trade-offs was observed in agricultural areas ($R^2 = 0.97$), followed by waterbodies ($R^2 = 0.74$) and vegetation cover ($R^2 = 0.68$). For regulating vs. cultural ES trade-offs, built-up regions exhibited the highest R^2 value (0.99) due to their aesthetic value, followed by vegetation cover ($R^2 = 0.98$) and waterbodies ($R^2 = 0.93$). No significant relationship was identified in bare land and agricultural land between these ES types. In provisioning vs. cultural ES trade-offs, the strongest relationship was found in waterbody areas ($R^2 = 0.90$), followed by vegetation cover ($R^2 = 0.78$), with no significant relationship identified in bare land areas.

This study utilized the Digital Building Height Model to calculate the vertical profile of the city, revealing that the most significant urban development occurred in the northwest and middle east parts of the study area. These vertical profile datasets were then used to measure the degree of urbanization through technomass. Technomass is a three-dimensional indicator encompassing human-made material stocks such as buildings and infrastructure. The volumes and rates of technomass showed positive trends both spatially and temporally, varying significantly across the study area from 6,213.52 m³/ha (the lowest in 2000 in the fringe area) to 105,432.15 m³/ha (the highest in 2021 in the OCBD region). A Geographically Weighted Regression (GWR) model was employed to analyze geographic spatial relationships between urbanization indicators (nighttime light data (NTL), population density (PD), and technomass) and changes in ecosystem service value (ESV). The local R^2 values, ranging from 0 to 1, indicated that technomass was the most suitable indicator for analyzing urbanization's impact on ESV ($r > 0.61$), followed by NTL ($r > 0.56$) and PD ($r > 0.54$). Pearson's correlation analysis revealed a significant negative correlation ($p < 0.01$) between ESV and the urbanization indicators. Technomass exhibited a strong negative association with ESV ($r > -0.96$), followed by PD ($r > -0.94$). Additionally, there was a significant positive correlation between technomass and NTL/PD, while the correlation between technomass/NTL/PD and ESV was negative. The study found that areas with higher urbanization levels experienced a significant decline in ESV. The highest rate of ESV decline (87.55%) was observed where urbanization intensified, with a net ESV

decrease of 68.34% and a technomass increase of 243.11% throughout the study period. Bivariate Local Indicators of Spatial Association (LISA) cluster maps indicated that areas with high urbanization levels corresponded with very low ESV values. This study highlights the effectiveness of using technomass analysis techniques to understand the spatiotemporal dynamic evolution of the relationship between urbanization and ESV. It suggests that the government should focus on various aspects of urbanization and selectively promote ecological protection, restoration, and construction within the identified spatial clustering areas.

The urban thermal environment in Dhaka city has been significantly impacted by rising urbanization and population growth. The research examined the spatiotemporal Surface Urban Heat Island (SUHI) phenomenon and evaluated the urban heat mitigation potential of ecosystem services using the InVEST Urban Cooling Model. Findings indicated that SUHI values in Dhaka are closely related to Land Use and Land Cover (LULC) classifications. Areas with the lowest SUHI values, primarily located around the urban fringe with abundant water, vegetation cover, and larger urban vegetation cover showed greater cooling. Intermediate SUHI values were found in the NI and NCBD areas, characterized by grasslands and water bodies. Conversely, the urban core, with minimal vegetation cover, exhibited the highest SUHI values. Over the study period, the mean SUHI increased in all LULC classes, with notable rises in built-up and bare land areas, from 2.75°C to 3.24°C and 1.12°C to 1.47°C, respectively, between 2000 and 2018. However, a significant reduction in SUHI values occurred in 2020 due to decreased commercial activities during the COVID-19 pandemic, with built-up areas dropping from 2.75°C to 1.01°C and bare soil from 1.12°C to 0.52°C. The InVEST UCM model was used to calculate the temporal changes in heat mitigation scenarios for Dhaka city, with the Cooling effects index ranging from zero to one (higher values indicating greater Cooling effects). Results showed a decrease in the average Cooling effects index from 0.57 to 0.30 between 2000 and 2020, reflecting a 47.55% reduction. Using GIS zonal statistics, the study found the highest heat mitigation index (HMI) in the rural-urban fringe area (69.85%) in 2000, and the lowest in the new industrial area (20.36%). Over the study period, the new industrial area experienced the most significant HMI decrease (-64.58%), followed by OCBD (-

62.42%), fringe areas (-44.37%), NCBD (-33.22%), and the inner city (-28.44%). The study highlighted that the conversion of vegetation cover to other land uses significantly reduced heat mitigation capacity, especially in fringe areas and newly developed central business districts (CBD). Regions with higher HMI were mostly found in areas with better hydrological conditions and vegetation cover. Pearson's correlation analysis showed a significant negative correlation ($p < 0.01$) between Land Surface Temperature (LST) and HMI ($r = -0.77$). The rural-urban fringe area exhibited the strongest negative correlation in HMI changes ($r > -0.70$), followed by the inner city ($r > -0.61$), NCBD ($r > -0.46$), OCBD ($r > -0.40$), and the NI region ($r > -0.06$). The study identified a robust negative association between LST and HMI changes across the entire study area, indicating that the conversion of natural land to artificial uses has reduced HMI values.

Overall, this research provides a comprehensive view of ecosystem services and urbanization patterns, highlighting their impact on ecosystem service values (ESV). Several solutions were proposed to address this degradation, with the prevention of converting natural land to artificial land being the most crucial. The findings suggest that integrating regional parameters into ESV calculations can yield more accurate estimations. These key insights offer valuable guidance for city planners and environmentalists in Dhaka and across Bangladesh to review and enhance environmental policies. The study also recommends introducing payment for ecosystem services (PES) schemes to incentivize the preservation and restoration of natural habitats, which will improve the city's environmental quality. Finally, the key findings of this research can be considered and widely applied not only in other cities of Bangladesh but also to other international ones that are facing difficulties and challenges in their ecosystem service management, especially in urban areas.

Keywords: Technomass, vertical growth (VG), Spatiotemporal, Ecosystem services value (ESV), Remote sensing, Land use land cover (LULC), Dhaka City.

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Table of Contents

Abstract.....	iv
Acknowledgments	viii
List of Figures.....	xiv
List of Tables.....	xvi
List of Key Abbreviations.....	xviii
Chapter 1.Introduction	1
1.1 Background	1
1.1.1 Ecosystem Services.....	1
1.1.2 Interactions Between Dhaka City’s People and Ecosystems	1
1.1.3 Economic Valuation of Ecosystem Services.....	2
1.1.4 Urbanization Impacts on Ecosystem Services	3
1.2 Research Questions	5
1.3 Research Goals and Objectives	5
1.4 Significance of the Research	6
1.5 Thesis Outline.....	7
Chapter 2. Study Area and Methodology	9
2.1 Geography and Climate.....	9
2.2 Ecosystem Services and Urbanization Status of Dhaka City	11
2.3 Methodology	12
2.3.1 Downscaling Nighttime light (NTL) and Surface urban Heat Island (SUHI) Data	15

Chapter 3. Spatiotemporal Horizontal Expansion of Dhaka City, Bangladesh	16
3.1 Introduction	16
3.2 Materials and Method.....	18
3.2.1 Study Area.....	18
3.2.2 Datasets	20
3.2.3 Spectral Signature for LULC Mapping.....	23
3.2.4 Trends of LULC Changes	24
3.3 Results and Discussion	25
3.3.1 Spatiotemporal Changes of Horizontal Growth of the City.....	25
3.3.2 Extent and Rate of LULC Change	28
3.3.2.1 2000-2007 LULC Changes	28
3.3.2.2 2007-2009 LULC Changes	29
3.3.2.3 2009-2012 LULC Changes	29
3.3.2.4 2012-2018 LULC Changes	30
3.3.2.5 2018-2021 LULC Changes	31
3.3.3 LULC change Matrix	32
3.3.4 Accuracy Assessment.....	34
3.3.5 Driving Factors of LULC Changes.....	35
3.4 Conclusions	35
Chapter 4. Assessment of Regional Ecosystem Service Value (ESV) and their Trade-offs in Dhaka City, Bangladesh.....	36
4.1 Introduction	36
4.2 Materials and Methods	38
4.2.1 Study Area.....	38
4.2.2 Datasets	39
4.2.3 Ecosystem Services Valuation	40
4.2.3.1 Identification of ES	40
4.2.3.2 Equivalent Weight Coefficient	40

4.2.3.3 Spatial Scale Correction for Revised Equivalent Weight Coefficient and Common International Classification of Ecosystem Services (CICES)	41
4.2.3.4 Calculating Regional Ecosystem Services	44
4.2.3.5 Trade-offs between Ecosystem Services Bundles	44
4.2.3.6 Ecosystem Sensitivity Analysis.....	45
4.3 Results and Discussion.....	46
4.3.1 Ecosystem Services Class Using the Common International Classification (CICES v5.1).....	46
4.3.2 Ecosystem Service Value of Dhaka City.....	48
4.3.3 Changes in Total Ecosystem Service Value (ESV).....	49
4.3.4 Supply and Changes in the Values of Ecosystem Service Classes in Dhaka.....	51
4.3.5 Trade-offs between Ecosystem Services (ES) bundles	52
4.3.5.1 Trade-offs between the provisioning and the regulating ES bundles	52
4.3.5.2 Trade-offs between regulating and cultural ES bundles	53
4.3.5.3 Trade-offs between provisioning and cultural ES bundles.....	55
4.4 Ecosystem Services Sensitivity Analysis	56
4.5 Conclusion.....	57
Chapter 5. Investigating the Spatiotemporal Patterns of the Degree of Urbanization and its Relationship with Ecosystem Service Values	58
5.1 Introduction	58
5.2 Materials and Methods	60
5.2.1 Study Area.....	60
5.2.2 Datasets	61
5.2.3 Description of the Datasets	62
5.2.3.1 SRTM DEM: The	62
5.2.3.2 ALOS PALSAR DEM:.....	63
5.2.3.3 AW3D30M DEM:	63
5.2.3.4 TanDEM-X DSM:	63
5.2.3.5 Ground-Based Data:	64
5.2.3.6 Multi-temporal datasets of VIIRS-DNB nighttime light:.....	64

5.2.4 Technomass Calculation to Quantify the Degree of Urbanization	65
5.3 Results and Discussion.....	66
5.3.1 Spatiotemporal Changes of Vertical Growth of the City	66
5.3.2 Spatiotemporal Patterns and Changes in the Urbanization Indicators of Population Density (Pd) and Nighttime Light (NTL) Data	67
5.3.3 Spatiotemporal Changes of Degree of Urbanization	69
5.3.4 Spatial Correlation between Urbanization Indicators and ES.....	70
5.3.5 Spatially Non-Stationary Response of ESV Changes to Degree of Urbanization	71
5.3.6 Spatiotemporal Relationship between ESV and Urbanization	72
5.4 Conclusion.....	74
Chapter 6. Evaluating the Cooling Potential of Ecosystem Services in Dhaka City, Bangladesh, to Mitigate Urban Heat Islands Resulting from Urbanization through Nature-Based Solutions	75
6.1 Introduction	75
6.2 Materials and Methods	78
6.2.1 Study Area.....	78
6.3 Identification of Ecosystem Functions and Components	80
6.4 Land Surface Temperature (LST) and LULC classification	80
6.5 Spatial Analysis of Surface Urban Heat Island (SUHI)	82
6.6 InVEST Urban Cooling Model	82
6.6.1 Model Parameterization and Data Sources	82
6.7 Assessment of the Cooling effects of Different Ecosystems.....	84
6.8 Spatial Correlation between Cooling effects of Vegetation cover and Heat Mitigation Index (HMI)	85
6.9. Results and Discussion.....	86
6.9.1 Characteristics of LULC and LST in Dhaka City.....	86
6.9.1.1 Spatial Characteristics of LULC	86
6.9.1.2 Spatial Pattern of Land Surface Temperature (LST).....	88

6.9.2 Spatial Characteristics of SUHI Changes over Different Land Classes	89
6.9.3 Spatiotemporal Heat Mitigation Pattern in Dhaka City.....	91
6.9.4 Spatiotemporal Assessment of HMI within Individual LULC Types.....	93
6.9.5 Correlation of HMI Changes Due to the LST.....	94
6.10 Conclusions	95
Chapter 7. Conclusion and Recommendations	96
7.1 Highlights of Results	96
7.1.1 Chapter 3: Spatiotemporal Horizontal Expansion of Dhaka City, Bangladesh .	96
7.1.2 Chapter 4: Assessing the Regional Value of Ecosystem Services (ESV) and their Trade-offs in Dhaka City, Bangladesh	97
7.1.3 Chapter 5: Investigating the spatiotemporal patterns of the degree of urbanization and their Relationship with ecosystem service values.....	98
7.1.4 Chapter 6: Evaluating the Cooling Potential of Ecosystem Services in Dhaka City, Bangladesh, for Nature-Based Mitigation of Urban Heat Islands Resulting from Urbanization.....	99
7.2 Recommendations	101
7.2.1 Prioritize Conservation and Restoration of Waterbodies.....	101
7.2.2 Expand Green Infrastructure and Preserve Vegetation cover Cover in Urban Planning	101
7.2.3 Encourage Compact, Vertical Urban Development	101
7.2.4 Strengthen Policy Framework for Ecosystem Service Valuation (ESV)	102
7.2.5 Utilizing Technomass for Monitoring Urban Growth.....	102
7.2.6 Implement Urban Heat Mitigation Measures in High SUHI Zones	102
7.3 Limitations and Future Scope.....	103
Appendices.....	104
References	117

List of Figures

Figure 1. 1 Research framework showing the flow of the study with key elements in each chapter.	8
Figure 2. 1 Study area (a) location of Bangladesh, (b) Bangladesh on nighttime light data (NTL), and (c) LULC of Dhaka (2021).....	10
Figure 2. 2 Methodological flow chart of the study.....	13
Figure 3. 1 Location of the Study Area from Google Satellite Hybrid	19
Figure 3. 2 Methodology of this study.....	22
Figure 3. 3 (a) LULC map of the study area (2000-2021), (b) Area (ha) of the major land classes	26
Figure 3. 4 LULC conversion matrix to the built-up area over the study period	33
Figure 4. 1 Ecosystem service value in Dhaka City (2021).....	39
Figure 4. 2 Spatially distributed total ESV (Million USD \$) in Dhaka from 2000-2021..	50
Figure 4. 3 The percentage of ESV decreases in Dhaka from 2000 to 2021	51
Figure 4. 4 a) Scatter plot and R^2 between provisioning and the regulating ESV by land use class. b) Supply of the provisioning ESV by land use class.....	53
Figure 4. 5 Scatter plot and R^2 between the regulating and cultural ESV by land use class. b) Supply of the regulating ESV by land use class.....	54
Figure 4. 6 Scatter plot and R^2 between Provisioning and cultural ESV by land use class.	56
Figure 5. 1 Built-up class on TanDEM image.....	60
Figure 5. 2 Workflow of the study	65
Figure 5. 3 Mean vertical growth (M) of the urban land zone in Dhaka city	66
Figure 5. 4 Spatial pattern and changes of urbanization indicators.	68
Figure 5. 5 Degree of urbanization using technomass indicator.....	69
Figure 5. 6 Coefficients of GWR between urbanization indicators and ESV changes.....	70
Figure 5. 7 Coefficients of GWR between the degree of urbanization and ESV changes.	72
Figure 5. 8 Bivariate LISA cluster maps between different types of urbanization indicators	

and ESV	73
Figure 6. 1 Study area (a) location of Bangladesh, (b) LULC of Dhaka (2020), and (c) HMI of Dhaka (2020).	79
Figure 6. 2 LULC maps of the study area (2000-2020).....	87
Figure 6. 3 Spatial pattern of Surface Urban Heat Island (SUHI) °C.....	89
Figure 6. 4 Mean SUHI over different LULC classes from 2000 to 2020.	90
Figure 6. 5 Spatially distributed heat mitigation index (HMI) in Dhaka from 2000-2020.	92
Figure 6. 6 Correlation between HMI and LST in Dhaka from 2000-2020	94

List of Tables

Table 3.1 Dataset used for LULC Classification	21
Table 3.2 LULC description (Costanza et al., 1997; de Groot et al., 2012; <i>ESVD</i> , 2023)	24
Table 3.3 Summary statistics of LULC in the study area from 2000 to 2021 (in hectares)	27
Table 3.4 Rate of LULC Changes between 2000-2007	28
Table 3.5 Rate of LULC Changes between 2007-2009	29
Table 3.6 Rate of LULC Changes between 2009-2012	30
Table 3.7 Rate of LULC Changes between 2012-2018	31
Table 3.8 Rate of LULC Changes between 2018-2021	32
Table 3.9 LULC conversion matrix between 2000-021.....	32
Table 4.1 Datasets used in this study.	40
Table 4.2 Correction Factors Used for Revising the Parameters.	41
Table 4.3 Equivalent ecosystems service and their corresponding CICES code in the study area.	43
Table 4.4 Equivalent ecosystems (LULC) and coefficients value at 2021 (US\$ <i>ha</i> – 1yr – 1) for ecosystem services values (ESV) per unit area with their respective CICES code (Costanza et al., 1997, 2014; de Groot et al., 2012; Sannigrahi et al., 2019; XIE Gao-di, 2008).	47
Table 4.5 Temporal ecosystem service value of the study area	48
Table 4.6 Total ecosystem services value (ESV) in (Million USD \$) by land use type and the change in Dhaka city from 2000 to 2021.....	49
Table 4.7 Percentage change of the total ESV values and sensitivity coefficient (CS) after a $\pm 50\%$ adjustment of value coefficients (VC) for each land use/land cover type in Dhaka City (2000–2021)	57
Table 5.1 Datasets used in this study.	62
Table 6.1 Datasets used in this study.	80
Table 6.2 Key parameters assigned to each land cover class within the study area are	

submitted to the model as the biophysical table.	83
Table 6.3 Thermal bands estimated mean zonal LST	88
Table 6.4 Mean distribution of HMI over different LULC classes from 2000 to 2020.....	93

List of Key Abbreviations

ES	Ecosystem Services
ESV	Ecosystem Service Value
PD	Population Density
NTL	Nighttime Light
RF	Random Forest
LULC	Land use Land Cover
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
FVC	Fractional Vegetation Cover
NDBI	Normalized difference Built-up Index
BSI	Bare Soil Index
GEE	Google Earth Engine
OSM	Open Street Map
VG	Vertical Growth
DBH	Digital Building Height
GWR	Geographically Weighted Regression Model
LST	Land Surface Temperature
HMI	Heat Mitigation Index
InVEST	Integrated Valuation of Ecosystem Services and Trade-Offs
SUHI	Surface Urban Heat Island
PES	Payment for Ecosystem Services
TEEB	The Economics of Ecosystems and Biodiversity
CICES	Common International Classification of Ecosystem Services
LISA	Local Indicators of Spatial Association

Chapter 1

Introduction

1.1 Background

1.1.1 Ecosystem Services

Ecosystem services are the benefits that humans derive from ecosystems as a form of provisioning, regulating, supporting, and cultural services (Braat & de Groot, 2012; Costanza et al., 2014; Duan et al., 2023) and serve as the basis of human survival and development (Y. He et al., 2021). The concept of ecosystem services (ES) is now widely recognized and endorsed by various international policy frameworks, including the post-2020 Global Biodiversity Framework (GBF, 2022), the United Nations Decade on Ecosystem Restoration (2021–2030) (UNEP & FAO, 2020), and the United Nations Sustainable Development Goals (SDG, 2024). These instruments emphasize the important role of ecosystem services in promoting societal well-being (Shrestha et al., 2023).

1.1.2 Interactions Between Dhaka City's People and Ecosystems

In Dhaka city, Bangladesh, rivers, lakes, and wetlands including the Buriganga, Turag, and Shitalakshya rivers, as well as Dhanmondi Lake are vital for water supply, biodiversity, and flood control (Abdullah et al., 2024). These water bodies support agriculture and fishing, which provide nutrition and livelihoods for urban communities (Chowdhury et al., 2020) and they act as natural water purification systems by filtering pollutants and maintaining groundwater levels (Brouwer et al., 2023). However, rapid urbanization has led to encroachment on these wetlands, threatening both the quality and availability of these vital water resources. Dhaka's vegetation cover, including parks and urban vegetation cover, play a vital role in moderating the city's temperature. Vegetation cover like Ramna Park and Suhrawardy Udyan provide cooling effects, enhance air quality by absorbing carbon dioxide, and contribute to mental well-being (Tabassum et al., 2024). These spaces also support biodiversity by providing habitats for native plant and animal species, though many of these areas face pressure from urban sprawl (Shammi et al., 2023).

In Dhaka's peri-urban areas, small-scale agriculture is common due to limited access

to fresh food. These green initiatives help improve food security and reduce dependency on food transported from rural areas, allowing residents access to fresh produce (Rahman et al., 2015). The city is also prone to frequent flooding due to heavy monsoon rains, compounded by its low elevation and proximity to rivers. Historically, the city's natural wetlands and floodplains served as natural buffers, absorbing excess rainwater (Alam et al., 2023). However, unplanned urban expansion has led to the filling of these floodplains, increasing vulnerability to floods. As a result, there is growing awareness of the need to protect and restore these ecosystems to ensure the city's resilience against climate change and natural disasters.

1.1.3 Economic Valuation of Ecosystem Services

Benefit of ecosystem services can be quantified by the economic valuation of their services (Kang et al., 2016; B. Li et al., 2022; W. Li et al., 2022; Song & Deng, 2017) and this can play an important role in the decision-making process (J. Chen et al., 2022; de Groot et al., 2012) including: a) Raising awareness among all stakeholders about the importance of natural capital for human well-being; b) Prioritizing objectives across policy targets; c) Developing policy instruments for environmental management, such as taxes, transferable quotas, certification, and labeling, and trade restrictions (Brander et al., 2024); d) Creating sustainable financing mechanisms, such as payments for ecosystem services (Gaglio et al., 2023); e) Nature-based solutions through cost-benefit analysis (Fennell et al., 2023); f) Quantifying the distribution of costs and benefits of management decisions among different stakeholders; g) Determining compensation for damage to nature (H. Yu et al., 2023). As people are more familiar with values expressed in monetary units, explicitly the monetary value of ecosystem services (ES) proves beneficial for enhancing decision-making processes, thereby consistently getting attention in both research and policy domains (Brander et al., 2024; Costanza et al., 2017). The economic value of these ecosystem services (ES) is the quantified net benefit people obtain from their utilization, regardless of whether there is a market transaction for the ES or not (Brander et al., 2024). Estimating the values of ecosystem services typically entails two stages: Firstly, measuring the biophysical provision of these services utilizing simplified indicators like land use or

ecological models such as soil conservation models; secondly, assigning economic values to these services through techniques like market prices, replacement costs, travel costs, contingent valuation, or benefit transfer methods (Schägnier et al., 2013), which can generally be divided into two categories primary data-based and unit value-based methods (Jiang, 2017; M. Yang et al., 2023). The primary data-based methods are mainly used for small spatial scale (Remme et al., 2015; L. Xie et al., 2022; Y. Zhang et al., 2018) or individual ecosystem services due to their complex accounting system and high data requirements (La Notte et al., 2017; Nedkov et al., 2022). Comparatively, the unit value-based method calculates the comprehensive ESV, using the ecosystem service value (ESV) per unit area and is more convenient for larger spatial scales (Anderson et al., 2017; Gashaw et al., 2018; Jiang et al., 2021; XIE Gao-di, 2008).

On this basis, scholars have studied the change in ecosystem service value in Bangladesh using the equivalent factor method which belongs to the unit value-based approach (Akber et al., 2018; Hoque et al., 2020; Morshed et al., 2022; Ziaul Hoque et al., 2022; Zinia & McShane, 2021). Nevertheless, the economic valuation of ES, especially considering regional parameters, remains an area requiring further investigation. Indeed, the same type of ecosystem in different regions can yield varying ES values due to regional differences in climate and the environment (X. Zhao et al., 2021). Methods to account for such regional differences are highly needed, especially when considering the monetary value of ES (ESV).

1.1.4 Urbanization Impacts on Ecosystem Services

Urbanization globally exerts pressures on ecosystems and stands as a significant driver of ecosystem change (W. Chen et al., 2023). Approximately 60% of the world's ES has declined due to increased anthropogenic activities (M. Yang et al., 2023), leading to diminished vegetation cover and an intensified urban heat island (UHI) effect in cities (Basu & Das, 2023). Urbanization has increased globally, from 24% in 1950 to 55% in 2018, and is expected to reach 67.2% by 2050 (UN, 2015; M. Yang et al., 2023). Researchers have identified that the degree of urbanization can be measured using different factors, with nighttime light data (NTL) (S. Huang et al., 2023) , population density (PD)

(Wu et al., 2023) , and technomass (Inostroza, 2014) being particularly significant. The city has transformed into a megacity, experiencing substantial population pressure due to rural-to-urban migration and rapid urbanization over the past four decades (Roy et al., 2018) . Due to this rapid urbanization and population pressure, this research explored these three indicators to determine the most suitable indicator for analyzing urbanization in the context of ESV analysis. Despite the undeniable importance of the ES concept in establishing resilience and sustainable urban planning for Dhaka, proper attention has not been dedicated to this topic.

Prior studies have investigated the impact of urbanization on ecosystem service value, considering horizontal expansion (Z. Huang et al., 2023; Pham & Lin, 2023; Wang et al., 2023) and exploring building height estimation for vertical growth analysis (X. Chen et al., 2023; W. Zhang et al., 2018). Additionally, vertical growth-based urbanization studies are common in the urban thermal environment (X. Chen et al., 2023), socioeconomic factors (W. Zhang et al., 2017), homogeneities, and diversities in spatial patterns of vertical profiles (C. Yang & Zhao, 2022), aligning with population growth (Zambon et al., 2019). However, the quantitative spatial relationship between urbanization degrees and ecosystem services still requires further investigation (Inostroza & Barrera, 2019).

To address this gap, this study ascertains the quantitative relationship between urbanization and ES in Dhaka City, Bangladesh. The study employed the Digital Building Height Model (DBH) (Misra et al., 2018), to calculate technomass, a spatially explicit three-dimensional indicator of urbanization, alongside population density (PD) and nighttime light data (NTL) to model the quantitative relationship between urbanization and the monetary value of ES.

The study utilized the global equivalent coefficient value and adjusted it with regional parameters to compute the ESV of Dhaka, incorporating this ESV assessment into the analysis of both horizontal and vertical growth. The city is highly vulnerable to climate change and human activities, which have induced significant land use land cover (LULC) changes, including shrinkage of waterbodies, vegetation cover, agricultural land, and expansion of urban built-up areas (Abrar et al., 2022; A. M. Dewan et al., 2012). However, the impacts of these dynamics on ESV using regional parameters have not been studied in

the quantitative relationship between urbanization and the monetary value of ES.

1.2 Research Questions

The research questions are as follows:

- To what extent do changes in land use land cover (LULC), including waterbody shrinkage, vegetation cover loss, and urban built-up area expansion, impact the monetary value of ecosystem services in Dhaka city, Bangladesh?
- What is the importance of regional parameters, such as climate and environmental factors, to calculate the monetary value of ecosystem services?
- How does the spatial distribution of urbanization indicators (technomass, population density, nighttime light data) correlate with the ecosystem services across different regions within Dhaka city, Bangladesh?
- What are the patterns of horizontal and vertical urban growth and the degree of urbanization in Dhaka city, Bangladesh?
- What are the implications of urbanization-induced changes on the provision of ecosystem services, such as urban heat mitigation in Dhaka city, Bangladesh?

1.3 Research Goals and Objectives

The overarching of this study is to investigate the relationship between urbanization and ecosystem services (ES) in Dhaka city, focusing on the impact of rapid urbanization on the provision of ecosystem services over time. Additionally, the research aims to develop models that illustrate the spatiotemporal dynamics between levels of urbanization and ecosystem service values (ESV) in Dhaka, incorporating regionally adjusted value coefficients. Using geographically weighted regression (GWR) modeling, the study seeks to determine the most appropriate indicators for analyzing urbanization concerning ESV analysis. Finally, the research evaluates the cooling potential of these ecosystem services for the nature-based mitigation of urban heat islands for healthy and resilient cities.

The specific objectives are as follows:

- To evaluate and quantify the vertical and horizontal metropolitan growth of Dhaka city from 2000 to 2021;
- Estimate the economic values of ecosystem services of a high-density city using the modified regional value coefficient;
- Evaluate the effects of spatiotemporal vertical and horizontal landscape changes on ESV; and
- To assess the Cooling effects of ecosystem services for nature-based mitigation of urban heat islands for a healthy and resilient city.

The coefficient of sensitivity was then assessed to explore the robustness of the results. The findings of the study will provide new insights to decision-makers to understand the interaction mechanism between ES and urbanization and provide references and suggestions for sustainable management of ecosystems.

1.4 Significance of the Research

The significance of the research lies in its exploration of the intricate quantitative relationship between urbanization and ecosystem services (ES) in Dhaka City, Bangladesh. As defined, ecosystem services are crucial for human survival and development and are recognized within international policy frameworks as essential for societal well-being. However, the economic valuation of these services, especially considering regional parameters, remains an area requiring further investigation. The absence of a current regional ecosystem services database poses difficulties to the sustainable urban development of Dhaka city. This research developed the regional ES database of Dhaka city.

Urbanization globally exerts immense pressure on ecosystems and is a significant driver of ecosystem change. Despite the recognition of the importance of ES in establishing resilience and sustainable urban planning, proper attention has not been dedicated to this topic in Dhaka. This research developed the spatiotemporal vertical and horizontal growth of the city that will help planners formulate the proper policy to ensure sustainable development.

By addressing research questions regarding the spatial distribution of urbanization indicators, patterns of urban growth, and the impact of land use changes on ES, this study will provide valuable insights for decision-makers. It evaluates the cooling potential of ecosystem services for mitigating urban heat islands, contributing to the creation of a healthy and resilient urban environment.

Overall, this research has the potential to inform policy formulation and sustainable urban development practices, ensuring the preservation of ecosystem services essential for human well-being and environmental health in Dhaka city.

1.5 Thesis Outline

This thesis comprises seven chapters, each contributing to the understanding of urbanization and ecosystem services in Dhaka City, Bangladesh. Chapter 1 serves as the introduction, providing background information on the topic. In Chapter 2, the study area and methodology employed in the research are outlined. Chapter 3 examines the spatiotemporal horizontal expansion of Dhaka city, focusing on the assessment of ecosystem service value (ESV). In Chapter 4, the spatiotemporal degree of urbanization in response to vertical growth is described. Chapter 5 examines the regional value of ecosystem services (ESV), explores trade-offs, and explains their relationship with the degree of urbanization. In Chapter 6, the Cooling effects of these ecosystem services for nature-based mitigation of urban heat islands are investigated. Finally, Chapter 7 describes comprehensive conclusions, highlighting limitations, and presenting opportunities in urban ecosystem service management.

These chapters represent significant scientific and methodological contributions to the existing literature on quantifying urbanization and its spatiotemporal relationship with ecosystem services. This research endeavor expands knowledge and serves as a reference for further exploration in the field of urbanization and ecosystem services, contributing to the pursuit of sustainable urban development.

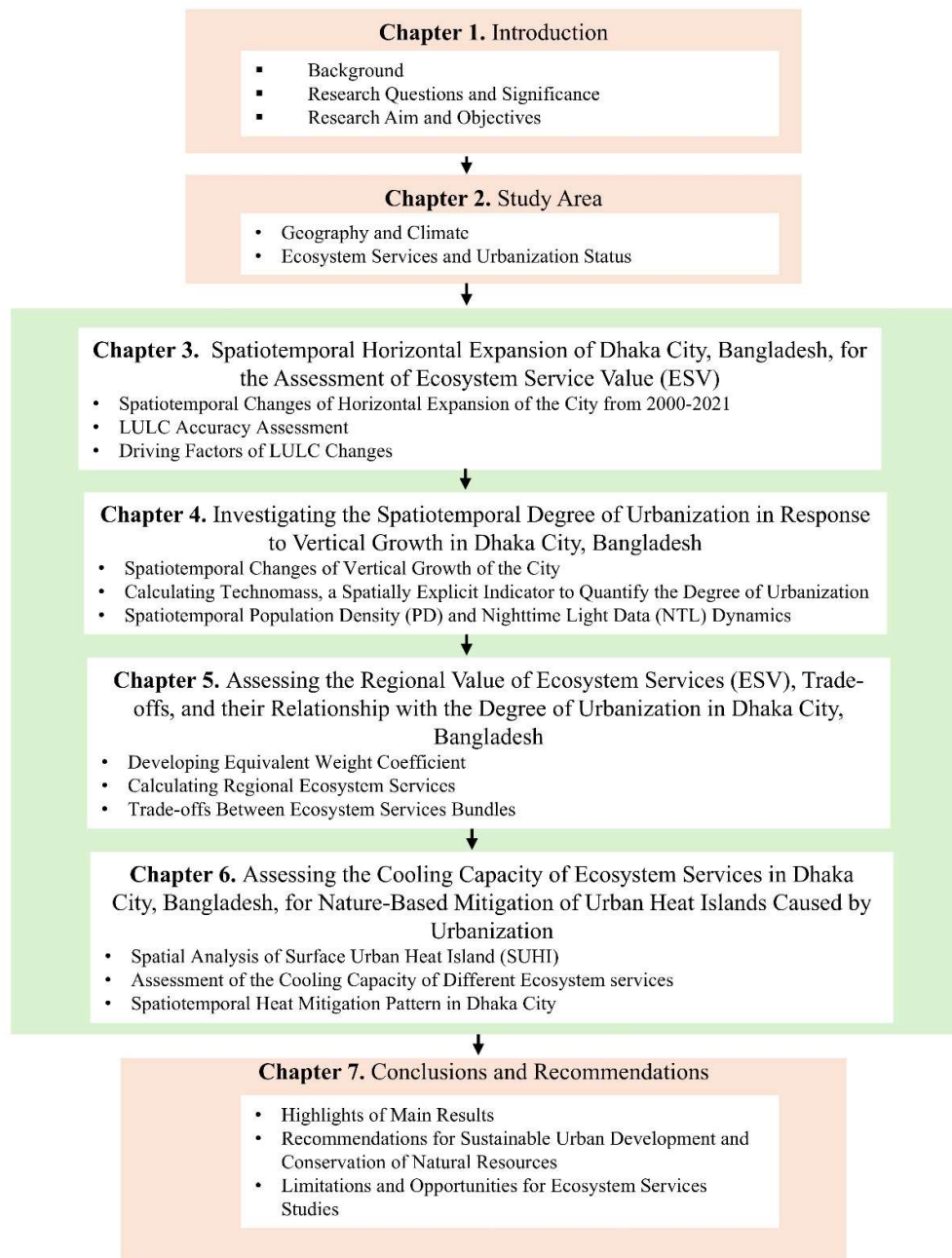


Figure 1. 1 Research framework showing the flow of the study with key elements in each chapter.

Chapter 2

Study Area and Methodology

2.1 Geography and Climate

Dhaka, the capital city of Bangladesh, is located between 23.71° N latitudes and 90.41° E longitudes (Fig.2. 1) and has a total area of 306.4 km² (Hossain et al., 2024). It is one of the most populated cities in Bangladesh and the world, with almost 22.47 million people (*Dhaka, Bangladesh Metro Area Population 1950-2022*, 190 C.E.a). The city includes two city corporations, namely Dhaka South City Corporation (DSCC with 57 wards) and Dhaka North City Corporation (DNCC with 36 wards) along with the fringe area with 17 unions. The study area is divided into five regions namely the old central business district (OCBD) area having Motijheel, Ramna, Dhanmondi, Agargaon; the newly developed CBD (NCBD) area having Gulshan, Banasree, Badda, Baridhara, Nikunja, new industrial (NI) area having Tejgaon, Begunbari; old housing and old industrial (Inner City) area having Bangshal, Jatrabari, Hazaribagh, Mohammadpur; rural-urban fringe (Fringe Area) having Khilgaon, Beraid, Dumni, Kanchkura, Uttar Khan, Mainertek, Bamnartek, Agunda, and Gabtoli (Capital city authority, Dhaka, Bangladesh, 2018; Rahman et al., 2021).

The city experiences a subtropical monsoon climate characterized by high temperatures, heavy rainfall, and distinct wet and dry seasons (A. Dewan, Kiselev, & Botje, 2021). It has warm temperatures throughout the year, with significant variations between the seasons. According to data from the Bangladesh Meteorological Department (BMD), the average annual temperature in Dhaka ranges from around 25°C to 28°C. Winter months, from December to February, are cooler with temperatures dropping to around 10°C to 20°C, providing relief from the scorching heat. Dhaka receives most of its rainfall during the monsoon season, which lasts from June to September. Its annual rainfall is about 2000mm and approximately 80% of it occurs during the monsoon (Murshed et al., 2011). The monsoon rains are crucial for agriculture and replenishing water sources but also pose challenges for infrastructure and urban planning due to flooding risks.

Humidity levels in Dhaka remain high throughout the year, particularly during the monsoon season. Relative humidity often exceeds 75% during the wet season, creating a muggy and uncomfortable environment (Sharmin et al., 2015).

The city is surrounded by three major rivers: Turag to the northwest, Buriganga-Dhaleshwari to the south, and Shitalakhya-Balu to the east. More than 80% area has been urbanized and the population density is 30,474 and 39,353 per square kilometer in the north and south city corporations (BBS, 2022).

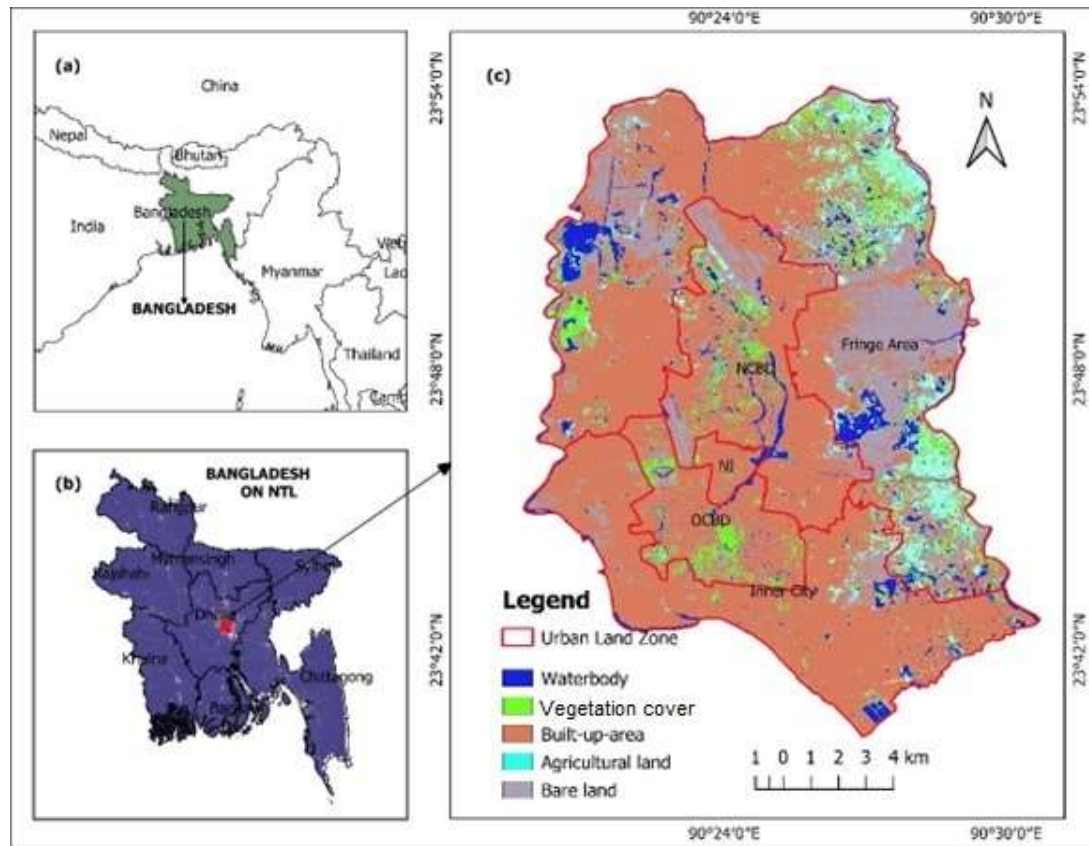


Figure 2. 1 Study area (a) location of Bangladesh, (b) Bangladesh on nighttime light data (NTL), and (c) LULC of Dhaka (2021)

To meet the demands of this huge population, the city is growing rapidly both vertically and horizontally (Rahman et al., 2020). The spatial expansion of the city has adverse impacts on ES, as well as microclimatic changes. Since its independence, the city has experienced continuous destruction of its parks, vacant lands, and green areas as a result of

rapid urban expansion (Byomkesh et al., 2012). This has led to a reduction in the wetlands and vegetation cover (Jahangir Alam & Akter Mullick, 2014; Shubho et al., 2015; Zinia & McShane, 2018). This consistent loss of natural habitat makes the city vulnerable to natural hazards and it also reduces the ES (Zinia & McShane, 2021).

2.2 Ecosystem Services and Urbanization Status of Dhaka City

Urban ecosystems are defined as all-natural, semi-natural, and artificial systems within the city that promote multiple effects such as health, well-being, and aesthetic benefits to urban dwellers (Ossola & Hopton, 2018). The continuous growth of cities around the world is causing urban fabric to expand. Globally, it is expected that 70% of the population will live in urban areas by 2050 (Leridon, 2020), presenting a significant challenge to the capacity of the global ecosystem to sustain resources and the environment. Many cities overlook the importance of maintaining natural ecosystems during their development processes. This neglect results in adverse impacts on the structure and functionality of these ecosystems, driven by escalating demands for food, energy, and water, as well as the development of resources, land use changes, pursuit of materialistic pleasures, and pollution emissions (Bhuiyan et al., 2024; Liu et al., 2023).

In recent years, Bangladesh has witnessed a remarkable increase in both the rate of urbanization and the total urbanized area, with Dhaka emerging as the focal point of this transformation. A study conducted in 2018 revealed that since 1991, the city has witnessed an additional 234 square meters of built-up area in its periphery, (Roy et al., 2021), leading to a doubling of the urbanized area in Dhaka by 2021 (Bhuiyan et al., 2024). However, this rapid and uneven development has led to Dhaka becoming one of the world's most densely populated cities. Because of this growth, undesirable urban sprawl, construction along riverbanks, and loss of vegetation cover have become prevalent side effects (Tanzir et al., 2024).

Over the past two decades, the city has experienced a decline in its vegetation cover by 30.77%, water bodies by 29.84%, and agricultural land by 42.97%. In contrast, the built-up area has expanded by 94.94% (Bhuiyan et al., 2024).

2.3 Methodology

As the thesis overview outlines, this study consists of four primary investigations employing diverse research methodologies to examine and explore sustainable urban development utilizing geospatial data. Moreover, the research aims to construct models illustrating the spatiotemporal dynamics between urbanization levels and ecosystem service values (ESV) in Dhaka, integrating regionally adjusted value coefficients. With these objectives, the study investigates the past and present land use land cover (LULC) analysis, quantifying urbanization through the technomass indicator, and assessing the city's spatiotemporal horizontal and vertical expansion and its effects on ecosystems. Consequently, the methods and databases utilized in this study exhibit significant diversity. Particularly, the research framework is structured into seven chapters: Chapter 1 provides the research background, Chapter 2 delineates the study area and overall methodology, Chapters 3 through 6 respectively present the findings of the four main investigations conducted, and Chapter 7 presents recommendations and suggestions. These chapters employ various approaches, techniques, and tools, including data-driven analytical techniques, regression modeling, and the use of different modeling and computer-based software applications. Their selection is primarily contingent upon data availability and desired outcomes. Figure 2.2 illustrates the main applied methods and target objectives, which are briefly summarized below. Further detailed information on their application is elaborated in the specific research sections of the chapters.

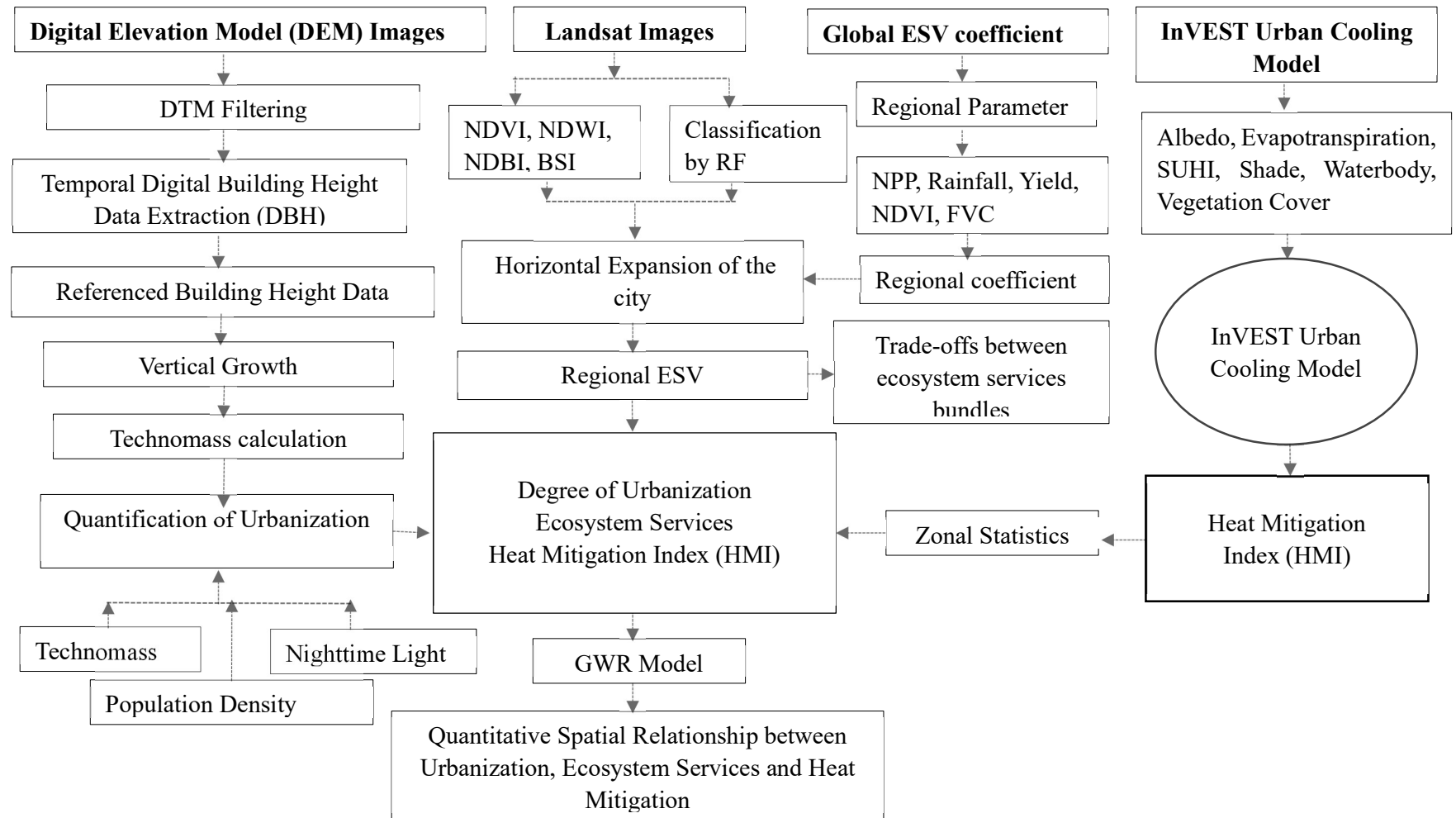


Figure 2. 2 Methodological flow chart of the study

In Chapter 3, the study begins with the spatiotemporal horizontal expansion of Dhaka City, Bangladesh, for the assessment of Ecosystem Service Value (ESV). Here temporal LULC changes are analyzed to calculate the ecosystem services value. Then the adjusted regional value coefficient is applied to calculate the ESV. Finally, key drivers were identified for temporal LULC changes.

In Chapter 4, the study applied the digital building height (DBH) to investigate the spatiotemporal degree of urbanization in response to vertical growth in Dhaka City, Bangladesh. This vertical growth data is applied to calculate the technomass, a spatially explicit indicator to quantify the degree of urbanization. Then spatiotemporal population density (PD) and Nighttime Light Data (NTL) were compared to identify which one is more effective in urbanization for ESV studies.

In Chapter 5, the study assessed the regional value of ecosystem services (ESV), trade-offs, and their relationship with the degree of urbanization in Dhaka City, Bangladesh. In this chapter, the research developed an equivalent weight coefficient for calculating regional ecosystem services. Finally, the research analyzed the trade-offs between ecosystem service bundles.

In Chapter 6, the study investigates into the cooling effects of ecosystem services in Dhaka City, Bangladesh, aiming at Nature-Based Mitigation of Urban Heat Islands (UHI). Within this chapter, the research studies the temporal Surface Urban Heat Island (SUHI) induced by urbanization and develops a model to depict its correlation with land surface temperature (LST). Subsequently, the study evaluates the Cooling effects of various ecosystem services utilizing the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model. Additionally, it formulates the Heat Mitigation Index (HMI) for the area, highlighting the significance of heat mitigation in facilitating sustainable urban development.

2.3.1 Downscaling Nighttime Light (NTL) and Surface Urban Heat Island (SUHI) Data:

This study utilized average radiance composite images derived from nighttime data of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) and Surface Urban Island (SUHI) data from the Global Surface UHI Explorer. Both datasets were initially available at coarse spatial resolutions: 464 meters for NTL and 300 meters for SUHI. To align with the resolution of other satellite imagery, the datasets were downscaled using the Google Earth Engine (GEE) platform, which applies nearest-neighbor resampling by default during reprojection. The VIIRS monthly composite nighttime light data was filtered, and the average radiance (avg_rad) was calculated for the selected period, clipped to the study area, and reprojected to a finer resolution of 30 meters, creating a high-resolution version (nighttime 30). A boxcar kernel with a 30-meter radius was applied through convolution to enhance spatial details, generating a smoothed high-definition nighttime light image (nighttime HD). The original, reprojected, and HD images were exported to Google Drive in the EPSG:4326 projection. Similarly, the Global Surface UHI (SUHI) data was downscaled to the desired resolution using the same procedure.

Chapter 3

Spatiotemporal Horizontal Expansion of Dhaka City, Bangladesh

3.1 Introduction

The sustainable development of the human economy and society cannot be achieved without the sustainable supply of ecosystem services (Yan Yan et al., 2017). However, recent years have witnessed a significant negative impact on ecosystem services due to the various human activities, with urbanization emerging as a primary causes (Xin et al., 2023). Alterations in the land use/land cover of specific areas directly affect the overall value of ecosystem services derived from those areas (Talukdar et al., 2020). Urban centers have undergone expansion since the latter half of the 20th century, with the most rapid urbanization occurring in developing nations (Cohen, 2006), In Dhaka city, for instance, urbanization has doubled over the past two decades (Bhuiyan et al., 2024). Temporal LULC changes play a significant role in identifying the urbanization pattern.

The conventional surveying techniques are challenging and costly to generate LULC maps. However, with remote sensing imagery, this task becomes significantly more manageable. There are two approaches to accomplishing this: supervised classification and unsupervised classification. In recent years, significant efforts have been made to simplify the process of LULC mapping with the aid of spectral indices (Zha et al., 2003). A spectral index can be calculated using two or more wavelength bands from remotely sensed satellite images. The indices serve as an indicator of the abundance of any desired feature (Santhosh & Shilpa, 2023). The Normalized Difference Vegetation Cover Index (NDVI), Normalized Difference Built-up Index (NDBI), Bare soil index (BSI), and Modified Normalized Difference Water Index (MNDWI) are the often-used indices. NDVI is used to identify the vegetative areas (Ezaidi et al., 2022), while MNDWI utilizes the visible green and near-infrared wavelength bands of satellite images to identify water bodies (Günen & Atasever, 2024). NDBI indices are utilized for identifying built-up areas, and BSI is employed for identifying bare soil (Wanhui Chen et al., 2004; Zha et al., 2003).

Urban ecosystems, which hold significant ecological, social, economic, and cultural importance at national, regional, and global levels, have been impacted by land use and land cover (LULC) changes (Hysa et al., 2024). This is especially evident in the conversion of natural habitats into urban settlements. Dhaka city serves as a typical example, where LULC changes are extensive, with agricultural lands and water bodies continuously transforming into urban settlements (Bhuiyan et al., 2024). Concurrently, a literature review was conducted to identify previous LULC statistics to validate the developed spatiotemporal LULC mapping. This chapter aims to identify the spatiotemporal horizontal expansion of Dhaka city using LULC classification. The specific objectives of this study are as follows:

1. To investigate the spatiotemporal horizontal expansion of the city using LULC change dynamics; and
2. To classify the LULC classes for ecosystem service value (ESV) calculation.

3.2 Materials and Method

3.2.1 Study Area

As presented in Chapter 2, Dhaka city is the 11th fastest-growing megacity in the world (H. M. Abdullah et al., 2024). Dhaka is located between 23.71° N latitude and 90.41° E longitude, near the center of Bangladesh. As the capital of the country, Dhaka is expanding faster than any other city in Asia, with an annual growth rate of 4.24%, driven by higher economic growth (Thorslund et al., 2017). Unplanned urbanization in Dhaka has destroyed natural areas, including most of the waterbodies and vegetation cover (Bhuiyan et al., 2024). The population of Dhaka increased from 3 million in 1980 to 18 million in 2018. Due to this rapid population growth, Dhaka has become one of the most densely populated cities in the world, with a current population of approximately 22.47 million people (Dhaka, Bangladesh Metro Area Population 1950-2022, 190 C.E.b). Land use land cover (LULC) of the study area is mainly composed of built-up areas, waterbodies, agricultural land, and bare soil.

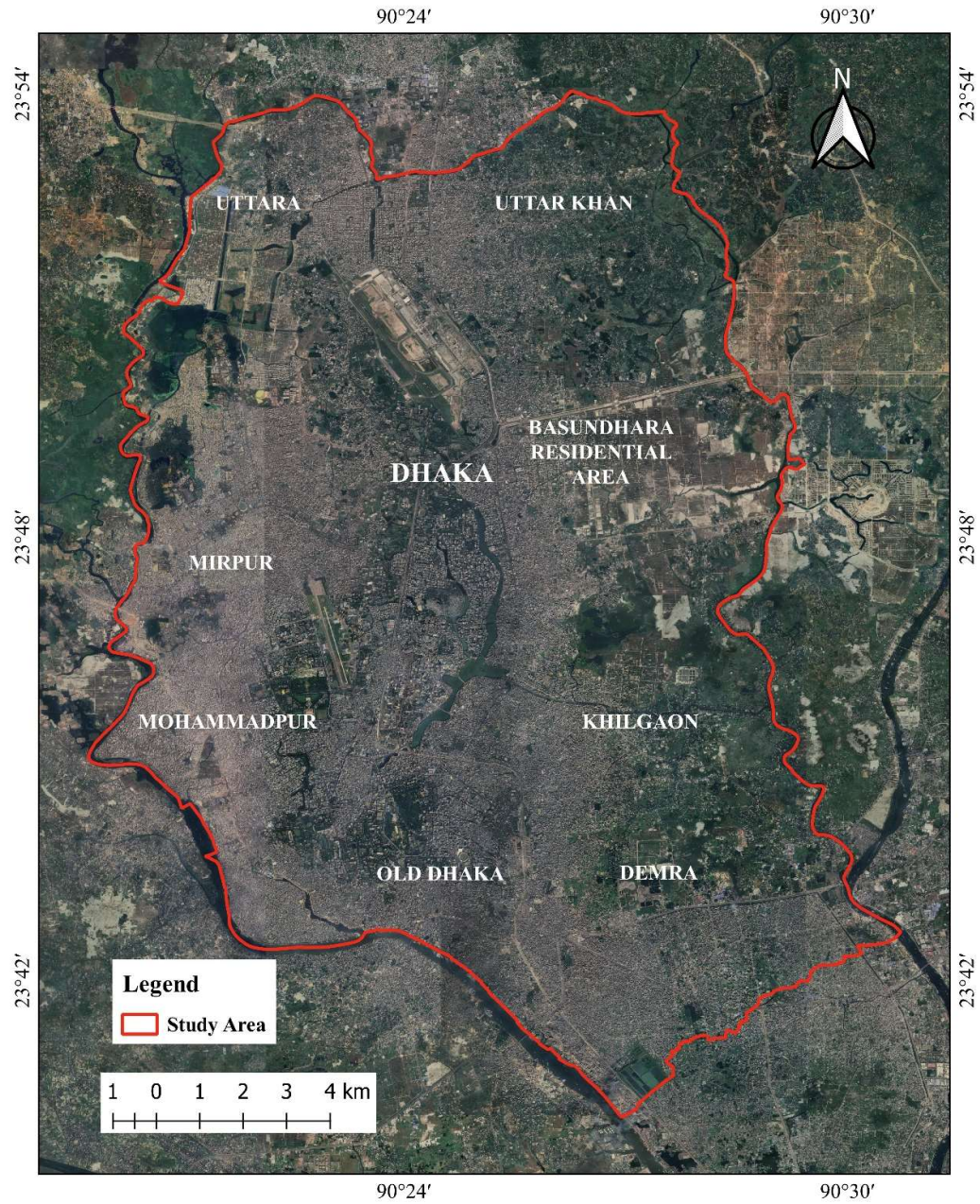


Figure 3. 1 Location of the Study Area from Google Satellite Hybrid

3.2.2 Datasets

A collection of temporal Landsat satellite images was used to generate the LULC classification for the study area, covering the period from 2000 to 2021. All preprocessing steps, including geometric correction, radiometric correction, and cloud masking, were conducted in Google Earth Engine (GEE). Since 2008, with the removal of monetary costs for accessing Landsat data, it has become one of the most widely known and publicly available sources of remotely sensed data. The United States Geological Survey (USGS) provides Landsat data, allowing users free access to Landsat 4–8 through GEE. GEE supports a variety of Landsat data processing methods, which are primarily categorized into at-sensor spectral radiance, TOA reflectance, and SR (Chander et al., 2009). USGS products are classified by quality into Real-Time (RT), Tier 2 (T2), and Tier 1 (T1). The Thematic Mapper (TM) sensor, Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) acquire data in the visible and infrared spectral regions for Landsat-4 and Landsat-5, Landsat-7, and Landsat-8, respectively. Six cloud-free Landsat images from satellites 5 to 8 were taken between 2000 and 2021. Table 3.1 describes the datasets used in this study for LULC classification.

The generated LULC maps were edited, processed, and analyzed using GIS software. To analyze changes, the LULC maps were compared in pairs by year. The methodology of this study is illustrated in Fig. 3.2, and the LULC classes are summarized according to the proxy classes described by Costanza et al (Costanza et al., 1997).

Previous LULC statistics, national database, Visible Infrared Imaging Radiometer Suite Day-Night Band (VIIRS-DNB) nighttime light data (NTL), ground-based building data, spectral indices, and OSM building footprint data were used for LULC classification and validation.

Table 3.1 Dataset used for LULC Classification

Data	Resolution	Sources	Acquisition Date
Landsat 5,8	30m	https://earthexplorer.usgs.gov/	2000,2007,2009, 2012,2018,2021
VIIRS-DNB	46 4 m	https://eogdata.mines.edu/products/vnl/#monthly	2021
An extended time series nighttime light data	464 m	Z. Chen et al., 2021	(2000–2020)
Ground-Based Building and Land Use Zoning Data	-	http://rajuk.portal.gov.bd/site/page/27748acb-1e72-4ea8-bfe3-0588d4e9f158	Building Data 2018 By Bangladesh Capital City Authority (RAJUK)
Open Street Map (OSM)		https://www.openstreetmap.org/#map=12/23.7838/90.4642	2021

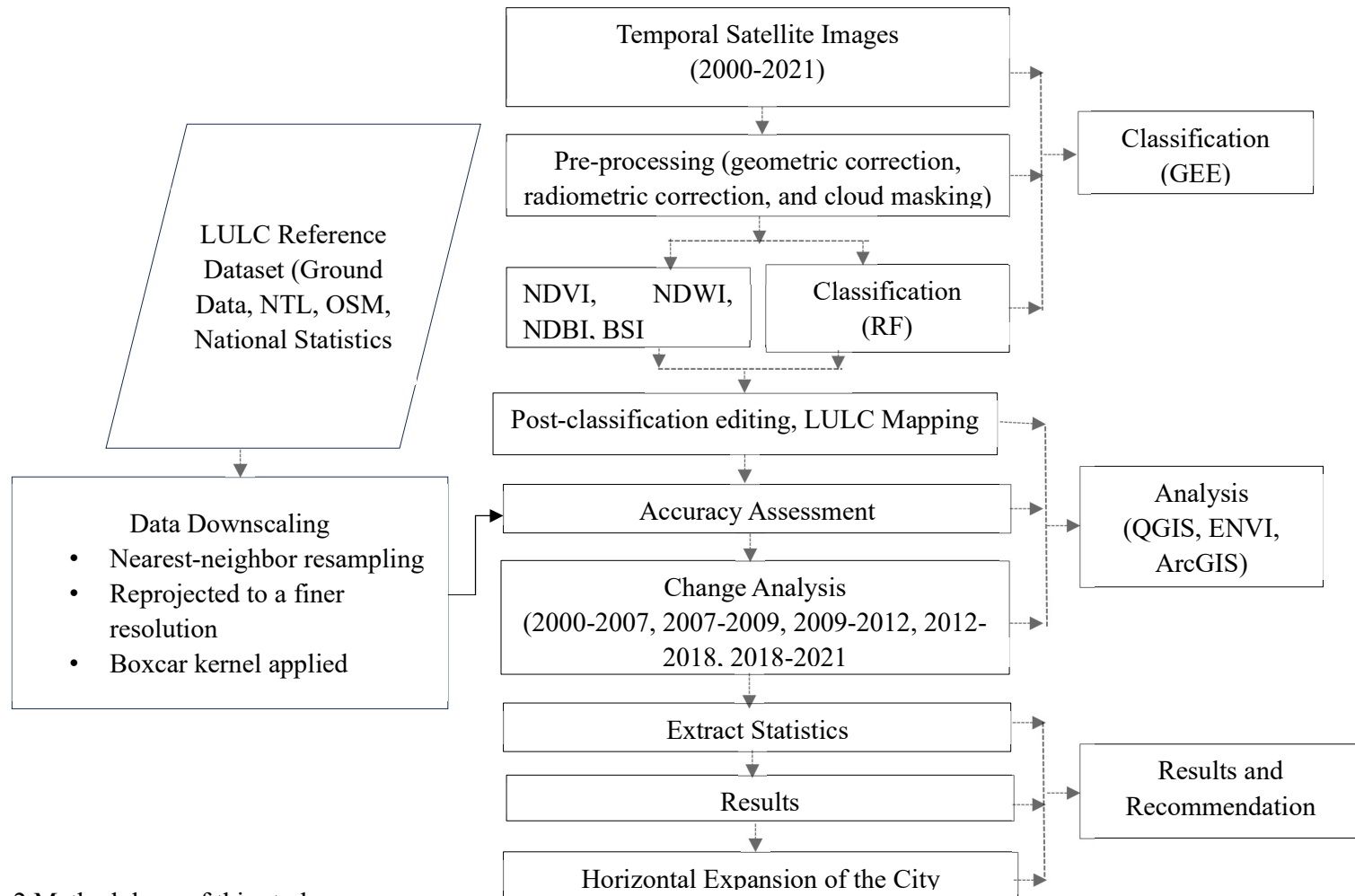


Figure 3. 2 Methodology of this study

3.2.3 Spectral Signature for LULC Mapping

Four radiometric indices from Landsat time series images, namely: normalized difference vegetation cover index (NDVI) (Ezaidi et al., 2022), modified normalized difference water index (MNDWI) (Haldar & Majumder, 2022), normalized difference built-up index (NDBI) (Zha et al., 2003) and bare soil index (BSI) (Wanhui Chen et al., 2004) were derived. These indices were incorporated into the image classification process for precise land use and land cover (LULC) classification on Google Earth Engine, employing a random forest (RF) classifier (Breiman, 2001). The generated LULC data were validated using Google Earth images and previously available national statistical datasets (BBS, 2022; Capital city authority, Dhaka, Bangladesh, 2018a). The ecosystems identified in the area comprised five LULC classes: water bodies, vegetation cover, built-up areas, agricultural land, and bare land. The accuracy of LULC classification for the study, assessed using the kappa coefficient, was 89.22% for producer accuracy and 87.23% for user accuracy.

The LULC classes were adopted from (Costanza et al., 1997; de Groot et al., 2012; *ESVD*, 2023) for ecosystem service value assessment, using these classes as representative biomes for each LULC type. These studies proposed 17 types of ecosystem service value coefficients for 16 biomes (LULC types), which were employed in their ecosystem service valuation model. In this study, each of the five LULC types from different reference years was matched with these representative biomes to obtain corresponding ecosystem service value coefficients. Additional land classes were sourced from the Economics of Ecosystems and Biodiversity (TEEB) valuation database (de Groot et al., 2012; Van der Ploeg & de Groot, 2010). A regional parameter was used to adjust the global coefficient values through the benefit transfer method, which involves using existing values and information from an original study site to estimate ecosystem service values (ESVs) for similar locations lacking specific valuation data (Kindu et al., 2016). To ensure the transferred data's applicability to this study's landscape conditions, only considered values from tropical areas with LULC

types like this geographical setting. The TEEB valuation database includes over 1300 original values compiled primarily from local studies worldwide (Van der Ploeg & de Groot, 2010). The most representative biome was used as a proxy for each LULC category (Table 3.2).

Table 3.2 LULC description (Costanza et al., 1997; de Groot et al., 2012; *ESVD*, 2023)

Land use/ Land cover	Description
Waterbody	River, lake, pond, canal, wetland, etc.
Vegetation cover	Trees, gardens, parks, etc.
Built-up-Area	Urban areas, residential, commercial, industrial areas, mixed-use, settlements, roads, man-made structures, etc.
Agricultural Land	Cropland, fallow land, etc.
Bare Land	Sandy field, newly transformed land for housing projects, etc.

3.2.4 Trends of LULC Changes

Changes in land use and land cover are crucial elements of global environmental change, reflecting the impact of human activities. Analyzing LULC change trends is essential for identifying which land use categories are being converted into others (Tewabe & Fentahun, 2020). Globally, LULC changes have been occurring since the dawn of human activity. However, the current rate of change is unprecedented due to significant developments in society and rapid population growth. The pace, extent, and intensity of these changes are now greater than ever before (Hailu et al., 2020).

Land use and land cover classification comparisons, from 2000 to 2007, 2007–2009, 2009–2012, 2012–2018, and 2018–2021 were used to analyze and detect the trend of changes in LULC in Dhaka city. The city area covered by each LULC class in various periods was compared. Then, for each LULC class, the direction of change was determined. The trend of LULC analysis provides information about the magnitude, extent, and trend of conversions in terms of temporally. The magnitude of the changes between two periods was used to compute the percentage and rate of changes Eq. (1)

LULC changes: A1-A2

$$\text{Rate of Change: } \frac{A1 - A2}{T} \times 100 \quad (1)$$

where *A1* is the area of LULC in period 1, *A2* is the area of LULC in period 2, and *T* is the period interval in years between *A1* and *A2*.

3.3 Results and Discussion

3.3.1 Spatiotemporal Changes of Horizontal Growth of the City

Land Use and Land Cover (LULC) classification was used for the analysis of the horizontal growth of the city. In Dhaka city, five major Land Use and Land Cover (LULC) types, waterbodies, vegetation cover, built-up areas, agricultural land, and bare land were classified from satellite images from 2000 to 2021 (Fig. 3.3). Table 3.3 provides a summary of the area coverage, in hectares (ha) and percentage (%), for each LULC class over this period.

In 2000, built-up areas and waterbodies were predominant, reaching 9,643.20 ha (31.47%) and 6,641.92 ha (21.68%), respectively. Vegetation cover, agricultural land, and bare land covered 6,239.63 ha (20.36%), 5,814.80 ha (18.98%), and 2,083.35 ha (6.80%), respectively.

By 2009, built-up areas and bare land had become the most extensive, covering 11,380.31 ha (37.14%) and 5,947.66 ha (19.41%), respectively. Vegetation cover, agricultural land, and waterbodies occupied 4,615.85 ha (15.06%), 3,814.78 ha (12.45%), and 4,664.30 ha (15.22%), respectively.

In 2021, the LULC classification showed built-up areas and bare land as the largest categories, covering 18,686.48 ha (60.99%) and 5,335.01 ha (17.41%), respectively. Vegetation cover, agricultural land, and waterbodies covered 1,920.15 ha (6.27%), 2,498.83 ha (8.16%), and 1,982.41 ha (6.47%), respectively (Table 3.3).

The conversion of vegetation cover to other land classes has been driven by the significant population increase in the city during the study period (Bhuiyan et al., 2024). Human activities have substantially reduced vegetation cover in many parts of Dhaka (Byomkesh et al., 2012).

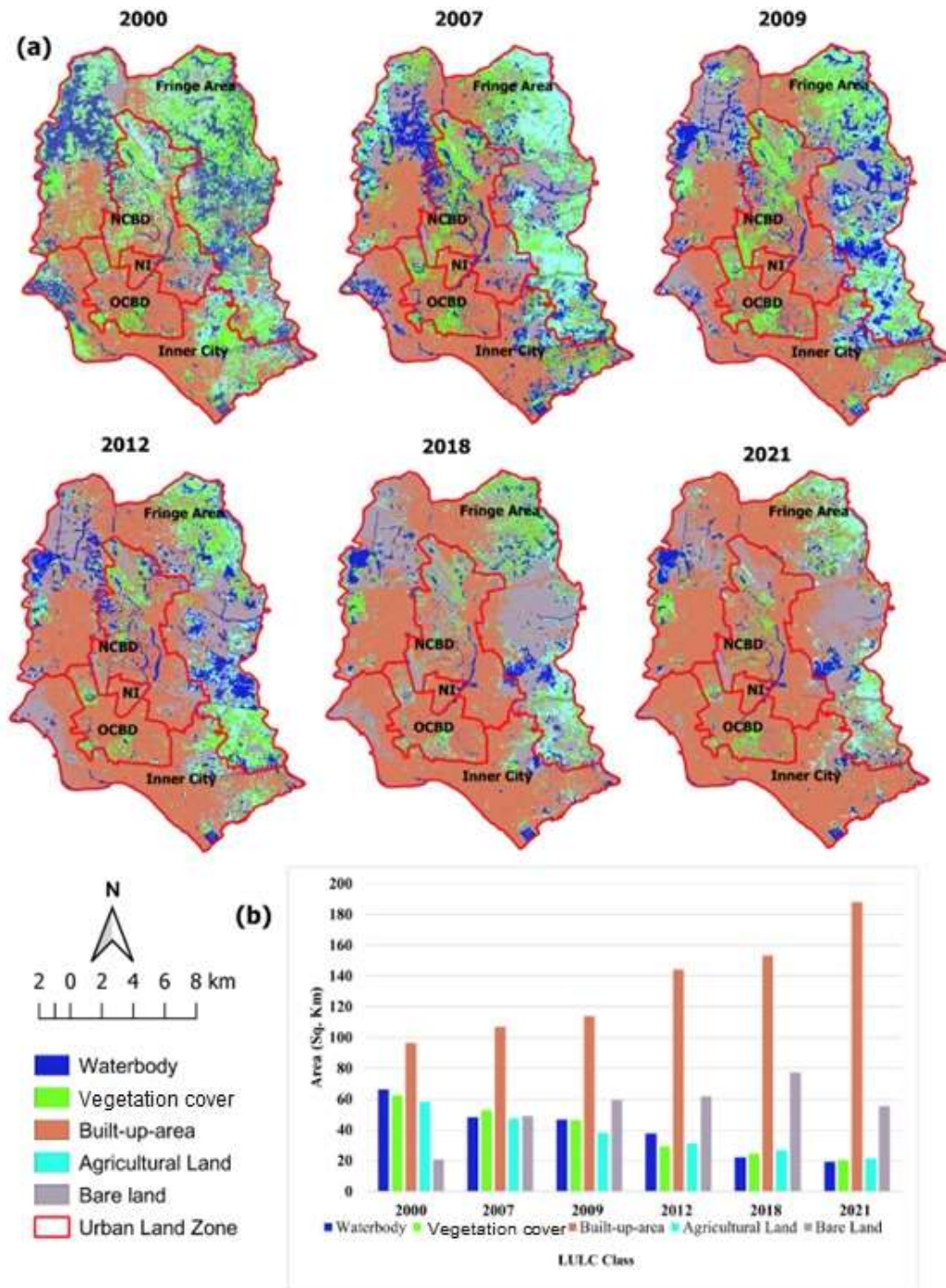


Figure 3. 3 (a) LULC map of the study area (2000-2021), (b) Area (ha) of the major land classes

Table 3.3 Summary statistics of LULC in the study area from 2000 to 2021 (in hectares)

LULC Class	Year											
	2000		2007		2009		2012		2018		2021	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Waterbody	6641.92	21.68	4822.76	15.74	4664.30	15.22	3763.61	12.28	2271.16	7.41	1982.41	6.47
Vegetation cover	6239.63	20.36	5267.16	17.19	4615.85	15.06	2938.91	9.59	2543.31	8.30	1920.15	6.27
Built up area	9643.20	31.47	10689.21	34.89	11380.31	37.14	14426.28	47.08	15307.72	49.96	18686.48	60.99
Agricultural land	5814.80	18.98	4751.72	15.51	3814.78	12.45	3116.27	10.17	2727.31	8.90	2498.83	8.16
Bare land	2083.35	6.80	4892.05	15.97	5947.66	19.41	6177.83	20.16	7572.89	24.72	5335.01	17.41

3.3.2 Extent and rate of LULC Change

For six time periods, the extent, and rates of changes for each LULC were summarized below: 2000-2007, 2007-2009, 2009-2012, 2012-2018, and 2018-2021 (Table 3.4-3.8). The dominant land uses that increased progressively over the study period were built-up areas that increased by 94.94%, whereas waterbody decreased by 70.93%. Bare land increased until 2018, after that it decreased due to its conversion to built-up areas. Agriculture land decreased by 60.08%, particularly in rural-urban fringe areas.

3.3.2.1 2000-2007 LULC Changes

Between 2000 and 2007, built-up areas and bare land in Dhaka City increased by 10.85% and 134.82%, respectively. Conversely, waterbodies, vegetation cover, and agricultural land decreased by 27.39%, 15.59%, and 18.28%, respectively (Table 3.4). This indicates a rising trend for built-up areas and bare land, while waterbodies, vegetation cover, and agricultural land declined. From 2000 to 2007, built-up areas and bare land expanded at rates of 149.3 ha/year (1.55%) and 401.24 ha/year (19.26%), respectively. Meanwhile, waterbodies, vegetation cover, and agricultural land decreased at rates of -259.88 ha/year (-3.91%), -138.92 ha/year (-2.23%), and -151.87 ha/year (-2.61%), respectively. These results align with previous research, showing that waterbodies, vegetation cover, and agricultural land in Dhaka are diminishing (Imran et al., 2021; Kafy et al., 2022). The reduction is primarily due to expanding settlements, worsening land degradation issues in developing countries (Nath et al., 2021).

Table 3.4 Rate of LULC Changes between 2000-2007

	2000	2007	Changes in 2000-2007		Rate of Changes	
	ha	ha	ha	%	ha/year	%
Waterbody	6641.92	4822.76	-1819.16	-27.39	-259.88	-3.91
Vegetation cover	6239.63	5267.16	-972.47	-15.59	-138.92	-2.23
Built up area	9643.20	10689.21	1046.01	10.85	149.43	1.55
Agricultural land	5814.80	4751.72	-1063.08	-18.28	-151.87	-2.61
Bare land	2083.35	4892.05	2808.71	134.82	401.24	19.26

3.3.2.2 2007-2009 LULC Changes

The extent and rate of LULC changes between 2007 and 2009 are detailed in Table 3.5. During this period, built-up areas and bare land increased by 6.47% and 21.58%, respectively. In contrast, water bodies, vegetation cover, and agricultural land decreased by 3.29%, 12.37%, and 19.72%, respectively. The expansion of built-up areas resulted from converting water bodies into settlements to accommodate the growing population, leading to land and soil degradation. Bare land also showed an increasing trend during this period. These findings align with a study by Imran et al. (Imran et al., 2021), who reported that the coverage of vegetation cover has been decreasing and increasing land surface temperature in this city.

Table 3.5 Rate of LULC Changes between 2007-2009

	2007	2009	Changes in 2007-2009		Rate of Changes	
	ha	ha	ha	%	ha/year	%
Waterbody	4822.76	4664.30	-158.47	-3.29	-22.64	-0.47
Vegetation cover	5267.16	4615.85	-651.30	-12.37	-93.04	-1.77
Built up area	10689.21	11380.31	691.11	6.47	98.73	0.92
Agricultural land	4751.72	3814.78	-936.94	-19.72	-133.85	-2.82
Bare land	4892.05	5947.66	1055.60	21.58	150.80	3.08

3.3.2.3 2009-2012 LULC Changes

Between 2009 and 2012, built-up areas and bare land in Dhaka City increased by 26.77% and 3.87%, respectively. Conversely, waterbodies, vegetation cover, and agricultural land decreased by -19.31%, -36.33%, and -18.31%, respectively (Table 3.6). This indicates a rising trend for built-up areas and bare land, while waterbodies, vegetation cover, and agricultural land declined. From 2009 to 2012, built-up areas and bare land expanded at rates of 435.14 ha/year (3.82%) and 32.88 ha/year (0.55%), respectively. Meanwhile, waterbodies, vegetation cover, and agricultural land decreased at rates of -128.67 ha/year (-2.76%), -239.56 ha/year (-5.19%), and -99.79 ha/year (-2.62%), respectively. These results align with previous research, showing that waterbodies, vegetation cover, and agricultural land in Dhaka are diminishing (Imran et al., 2021; Kafy et al., 2022). The

reduction is primarily due to expanding settlements, filling up water bodies, and converting bare land to housing projects.

Table 3.6 Rate of LULC Changes between 2009-2012

	2009	2012	Changes in 2009-2012		Rate of Changes	
	ha	ha	ha	%	ha/year	%
Waterbody	4664.30	3763.61	-900.69	-19.31	-128.67	-2.76
Vegetation cover	4615.85	2938.91	-1676.94	-36.33	-239.56	-5.19
Built up area	11380.31	14426.28	3045.97	26.77	435.14	3.82
Agricultural and	3814.78	3116.27	-698.51	-18.31	-99.79	-2.62
Bare land	5947.66	6177.83	230.17	3.87	32.88	0.55

3.3.2.4 2012-2018 LULC Changes

The extent and rate of LULC changes between 2012-2018 are detailed in Table 3.7. During this period, built-up areas and bare land increased by 6.11% and 22.58%, respectively. In contrast, water bodies, vegetation cover, and agricultural land decreased by -39.65%, -13.46%, and -12.48%, respectively. The expansion of built-up areas resulted from converting water bodies into bare land and then settlements to accommodate the growing population. Bare land also showed an increasing trend during this period. From 2012-2018, built-up areas and bare land expanded at rates of 125.92 ha/year (0.87%) and 199.29 ha/year (3.23%), respectively. Meanwhile, waterbodies, vegetation cover, and agricultural land decreased at rates of -213.21 ha/year (-5.66%), -56.51 ha/year (-1.92%), and -55.57 ha/year (-1.78%), respectively. These findings align with a study by (Rahaman et al., 2023) , who reported that this unplanned urbanization has a great impact on the inhabitants of Dhaka city.

Table 3.7 Rate of LULC Changes between 2012-2018

	2012	2018	Changes in 2012-2018		Rate of Changes	
	ha	ha	ha	%	ha/ year	%
Waterbody	3763.61	2271.16	-1492.45	-39.65	-213.21	-5.66
Vegetation cover	2938.91	2543.31	-395.60	-13.46	-56.51	-1.92
Built up area	14426.28	15307.72	881.44	6.11	125.92	0.87
Agricultural and	3116.27	2727.31	-388.96	-12.48	-55.57	-1.78
Bare land	6177.83	7572.89	1395.06	22.58	199.29	3.23

3.3.2.5 2018-2021 LULC Changes

During this period, bare land decreased as it was converted to housing projects, primarily in the northwestern and middle eastern parts of the city. Agricultural land declined by 8.38%, and vegetation cover decreased from 8.30% in 2018 to 6.27% in 2021. Between 2018 and 2021, built-up areas in Dhaka City increased by 22.07%. Conversely, water bodies, vegetation cover, agricultural land, and bare land decreased by 12.71%, 24.50%, 8.38%, and 29.55%, respectively (Table 3.8). This indicates an upward trend for built-up areas, while water bodies, vegetation cover, bare land, and agricultural land declined. From 2018 to 2021, built-up areas expanded at a rate of 482.68 ha/year (3.15%). Meanwhile, water bodies, vegetation cover, bare land, and agricultural land decreased at rates of 41.25 ha/year (1.82%), 89.02 ha/year (3.50%), 319.70 ha/year (4.22%), and 32.64 ha/year (1.20%), respectively. These findings reveal that, apart from urban built-up areas, all other land classes are rapidly decreasing. The reduction in urban vegetation cover and water bodies significantly impacts Dhaka's environment (Bhuiyan et al., 2024).

Table 3.8 Rate of LULC Changes between 2018-2021

	2018	2021	Changes in 2018-2021		Rate of Changes	
	ha	ha	ha	%	ha/year	%
Waterbody	2271.16	1982.41	-288.75	-12.71	-41.25	-1.82
Vegetation cover	2543.31	1920.15	-623.16	-24.50	-89.02	-3.50
Built up area	15307.72	18686.48	3378.76	22.07	482.68	3.15
Agricultural and	2727.31	2498.83	-228.48	-8.38	-32.64	-1.20
Bare land	7572.89	5335.01	-2237.88	-29.55	-319.70	-4.22

3.3.3 LULC change Matrix

The LULC change matrix illustrates the distribution of major transitions among the five LULC classes in the study area from 2000 to 2021 (Table 3.9). Most conversions initially turned land into bare land, which was subsequently transformed into built-up areas. This research quantifies these conversions to built-up areas, highlighting the city's horizontal expansion. Waterbodies and agricultural land were first converted to bare land, leading to a significant increase in bare land until 2012. However, from 2018 to 2021, most of the bare land was converted to built-up areas (Fig 3.4).

Table 3.9 LULC conversion matrix between 2000-2021.

	2000 to	2007 to	2009 to	2012 to	2018 to
	2007	2009	2012	2018	2021
	ha	ha	ha	ha	ha
Agricultural land to Built-up	1255.13	174.54	472.60	409.15	655.63
Bare Land to Built-up	618.38	833.32	1666.28	2139.36	3383.90
Vegetation cover to Built-up	943.32	786.94	1231.61	338.43	520.06
Waterbody to Built-up	407.27	525.87	715.64	454.66	125.95

This study revealed notable differences among the five LULC classes, with bare land

having the highest conversion rate between 2000 and 2021, accounting for 48.94% (8,641.24 ha) of its total area. During the same period, 2,967.04 ha (16.80%) of agricultural land, 3,820.36 ha (21.64%) of Vegetation cover, and 2,229.39 ha (12.63%) of waterbodies were converted to built-up areas. Agricultural land had the highest transition in 2000, with 1,255.13 hectares converted. Overall, waterbodies experienced a 70.93% decrease, as they were mostly converted to other land classes.

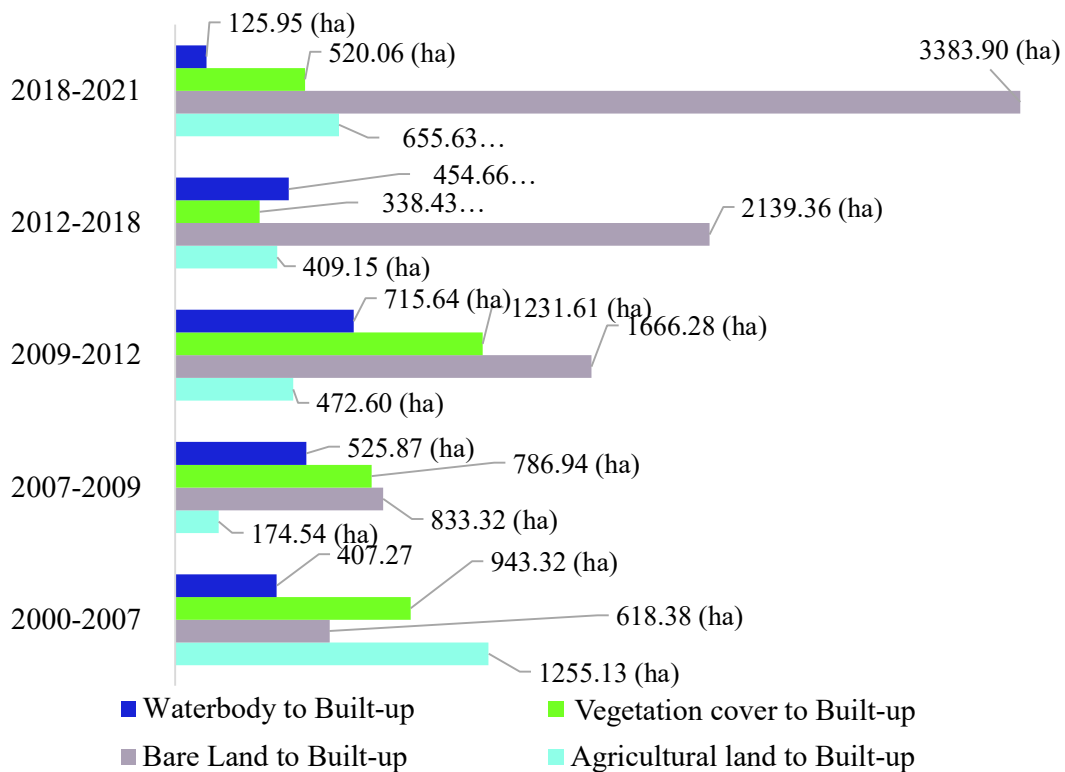


Figure 3. 4 LULC conversion matrix to the built-up area over the study period

3.3.4 Accuracy Assessment

The Worldview 3 image (30 cm) from 2021 was used to assess the spectral indices signature. A total of 373 reference data points from ground truth and spectral indices were selected to ensure adequate representation of all five LULC classes. These reference ground truth data points were chosen to appear consistently in Landsat images, Worldview images, and Google Earth maps. The ecosystems identified in the area comprised five LULC classes: water bodies, vegetation cover, built-up areas, agricultural land, and bare land. The accuracy of the LULC classification for the study, assessed using the kappa coefficient, was 89.22% for producer accuracy and 87.23% for user accuracy.

To assess the consistency of land use and land cover classification, it compared with the findings of several other studies conducted in the same city. In their study, (Hassan & Southworth, 2017) The proportion of water bodies in the urban growth trajectories of Dhaka city was estimated at 21.69% in 2000, which was similar to this research estimate of 6,641.92 ha (21.68%) for the same year. (Ahmed et al., 2013) observed in their research that the built-up area accounted for 37% in 2009, which aligned with this study's finding of 11,380.31 ha (37.14%) for the same year. The Capital City Development Authority of Dhaka city (RAJUK) identified 12% of water bodies in 2012, as reported in the Dhaka Structure Plan for 2016-2035 (Detailed Area Plan, 2016), which was close to this research result of 3,763.61 ha (12.28%) for the same year. (Rahman et al., 2020) estimated that built-up areas accounted for 47%, while agriculture and water bodies accounted for 11% and 12% respectively. This research analysis showed built-up areas of 14,426.28 ha (47.08%), agriculture of 3,116.27 ha (10.17%), and water bodies of 3,763.61 ha (12.28%) for 2012. In their 2022 study on the impact of heat vulnerability in Dhaka city, (Abrar et al., 2022) reported that the built-up area in 2021 was 62%, which was in line with this research classification of 18,798.63 ha (61.35%) for the same year. These findings indicate that changes in water bodies, agricultural land, and vegetation cover, which lead to diverse land use and land cover patterns, significantly decrease in Dhaka city, consistent with previous studies.

3.3.5 Driving Factors of LULC Changes

The population of Dhaka city is growing fast, causing significant environmental damage. Over the past four decades, Dhaka has evolved into a megacity, experiencing intense population pressure due to rural-to-urban migration and rapid urbanization (Roy et al., 2018) . Discussions with agricultural office experts, key informants, local respondents, and community leaders indicate that population growth and unplanned urbanization are the primary drivers of natural resource degradation in Dhaka. To accommodate this population pressure, the city is expanding rapidly both horizontally and vertically (Bhuiyan et al., 2024). The research found that most land classes have been converted to built-up areas to accommodate the growing population. Additionally, the adverse impacts of LULC changes are linked to human activities and urban expansion, resulting in biophysical degradation of soil, water, and the environment. This finding aligns with other studies (Rahaman et al., 2023).

The study reveals that one of the main factors of LULC change is the conversion of water bodies to bare land and then to built-up areas (48.94%). These changes have led to land degradation, soil erosion, biodiversity loss, damage to ecosystem services, and alterations to the hydrological cycle. The conversion of water bodies and vegetation cover to built-up areas has resulted in severe land degradation and biodiversity loss in Dhaka.

3.4 Conclusions

In conclusion, this study examined the spatiotemporal horizontal expansion of Dhaka city using geospatial technologies. The findings revealed a significant increase in built-up land (94%) and a concurrent decrease in water bodies, vegetation cover, and agricultural land over the study period. These changes worsen biodiversity loss, land degradation, and disruption of the hydrological cycle in the area. The data provided insight into the rate and distribution of urban expansion in the city. This information can assist policymakers and urban planners in developing sustainable urban management strategies and contribute to achieving Sustainable Development Goal 11 (Sustainable Cities and Communities).

Chapter 4

Assessment of Regional Ecosystem Service Value (ESV) and their Trade-offs in Dhaka City, Bangladesh

4.1 Introduction

Ecosystem services (ES) are the benefits that humans receive from ecosystems and are fundamental for well-being (Costanza et al., 2017). These benefits can be quantified in more than 50 different ways (IPBES, 2022) being the monetary valuation of a common practice (W. Li et al., 2022) in the decision-making process (J. Chen et al., 2022). ES valuation can be categorized into primary data-based and unit value-based methods (M. Yang et al., 2023), with most studies focusing on the unit value-based approach (Grammatikopoulou et al., 2023), while numerous assessments have utilized regional parameters (G. Xie et al., 2017). Previous studies in Bangladesh have primarily employed the benefit transfer method (BTM) within the unit value-based approach (S. Abdullah et al., 2022; Akber et al., 2018; Hoque et al., 2020; Morshed et al., 2022; Ziaul Hoque et al., 2022; Zinia & McShane, 2021).

At the same time, urbanization globally exerts pressure on ecosystems and stands as a significant driver of ecosystem change (W. Chen et al., 2023). Approximately 60% of the world's ES has declined due to increased anthropogenic activities (M. Yang et al., 2023), leading to diminished vegetation cover and an intensified urban heat island (UHI) effect in cities (Basu and Das, 2023). Researchers have identified that the degree of urbanization can be measured using different factors, with nighttime light data (NTL) (S. Huang et al., 2023), population density (PD) (Wu et al., 2023), and technomass (Inostroza, 2014) being particularly significant. Dhaka has transformed into a megacity, experiencing substantial population pressure due to rural-to-urban migration and rapid urbanization over the past four decades (Roy et al., 2018). Despite the undeniable importance of the ES concept in establishing resilience and sustainable urban planning for Dhaka, proper attention has not been dedicated to this topic. Nevertheless, the economic valuation of ES, especially considering regional parameters, remains an area requiring further investigation. Indeed,

the same type of ecosystem in different regions can yield varying ES values due to regional differences in climate and the environment (X. Zhao et al., 2021). Methods to account for such regional differences are highly needed, especially when considering the monetary value of ES (ESV).

To address this gap, the quantitative relationship between urbanization and ES in Dhaka City, Bangladesh was ascertained. A global equivalent coefficient value was used and adjusted with regional parameters to compute the ESV of Dhaka, incorporating this ESV assessment into the analysis of both horizontal and vertical growth. The city is highly vulnerable to climate change and human activities, which have induced significant land use land cover (LULC) changes, including shrinkage of waterbodies, vegetation cover, agricultural land, and expansion of urban built-up areas (Abrar et al., 2022; A. M. Dewan et al., 2012). However, the impacts of these dynamics on ESV using regional parameters have not been studied in the quantitative relationship between urbanization and the monetary value of ES. Thus, the objectives of this study were as follows:

1. To develop equivalent value coefficients for this region.
2. To evaluate and quantify the ecosystem service value (ESV) of a high-density city using the modified regional value coefficient.
3. To analyze the trade-offs between ecosystem service bundles.
4. To assess the coefficient of sensitivity to explore the robustness of the results.

The findings of the study will provide new insights to decision-makers, helping them understand the interaction mechanisms of ecosystem services and their trade-offs in a highly urbanized city. It will also provide insights on how to integrate regional parameters for evaluating regional ecosystem services to ensure sustainable ecosystem management.

4.2 Materials and Methods

4.2.1 Study Area

Dhaka, the capital city of Bangladesh, is located between 23.71° N latitudes and 90.41° E longitudes (Fig. 1), covering a total area of 306.4 km² (Hossain et al., 2024). It is the most populated city in Bangladesh and one in the world, with almost 22.47 million people (Dhaka, Bangladesh Metro Area Population 1950-2022). The city is administratively divided into two city corporations: Dhaka South City Corporation (DSCC with 57 wards) and Dhaka North City Corporation (DNCC with 36 wards) with 17 unions. The study area is further categorized into five regions: the old central business district (OCBD) area, comprising Motijheel, Ramna, Dhanmondi, and Agargaon; the newly developed CBD (NCBD) area, including Gulshan, Banasree, Badda, Baridhara, Nikunja; the new industrial (NI) area, with Tejgaon and Begunbari; the old housing and old industrial (Inner City) area, encompassing Bangshal, Jatrabari, Hazaribagh, and Mohammadpur; and the rural-urban fringe (Fringe Area), covering Khilgaon, Beraid, Dumni, Kanchkura, Uttar Khan, Mainertek, Bamnartek, Agunda, and Gabtoli (Capital city authority, Dhaka, Bangladesh, 2018) More than 80% of the area has undergone urbanization, with population densities reaching 30,474 and 39,353 inhabitants per square kilometer in the north and south city corporations, respectively (BBS, 2022). To meet the demands of this population, the city is experiencing rapid expansion both vertically and horizontally (Rahman et al., 2020). Unfortunately, the city has been consistently losing its parks, vacant lands, and green areas (Byomkesh et al., 2012). This consistent loss makes the city vulnerable and also reduces the provision of ecosystem services (Zinia & McShane, 2021).

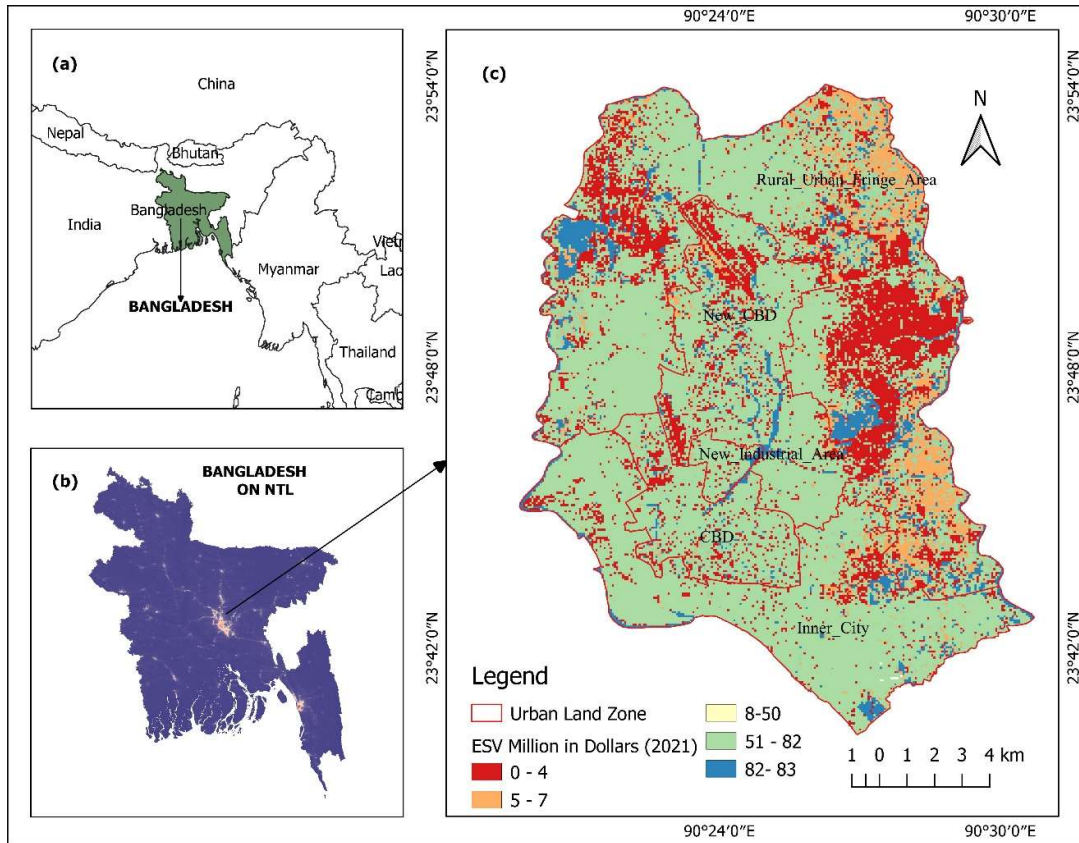


Figure 4. 1 Ecosystem service value in Dhaka City (2021)

4.2.2 Datasets

Remote sensing data with different spectral and spatial resolutions, along with various types of published and national datasets, were utilized to analyze the ecosystem service value of the city (Table 4. 1).

Table 4.1 Datasets used in this study.

Data	Resolution	Sources	Acquisition Date
Landsat 5,8	30m	https://earthexplorer.usgs.gov/	2000-2021
VIIRS-DNB	464 m	https://eogdata.mines.edu/products/vnl/#monthly	2021
An extended time series nighttime light data	464 m	Z. Chen et al., 2021	(2000–2020)
Land zone Data	-	http://rajuk.portal.gov.bd/site/page/27748acb-1e72-4ea8-bfe3-0588d4e9f158	Bangladesh Capital City Authority (RAJUK)

4.2.3 Ecosystem Services Valuation

4.2.3.1 Identification of ES

17 ES identified using the common international classification (CICES v5.1) (Haines-Young & Potschin-Young, 2018) (Table 3.2). This value has been calibrated with the per-unit value coefficient for each of the five LULC categories of five regions in the study area. A revised equivalent value coefficient was used to determine the equivalent weight coefficient (Table 4.2) for each ES (Table 3.2) for the temporal reference years.

4.2.3.2 Equivalent Weight Coefficient

Equivalent weight coefficients were used for the monetary valuation of each ES. The ESV per unit area was calculated by multiplying the corresponding equivalent coefficient by standard factors (G. Xie et al., 2017). US Department of Labor Consumer Price Index was used for the Inflation Calculator (https://www.bls.gov/data/inflation_calculator.htm) to adjust inflation.

4.2.3.3 Spatial Scale Correction for Revised Equivalent Weight Coefficient and Common International Classification of Ecosystem Services (CICES)

The Common International Classification of Ecosystem Services (CICES) provides a structured framework for naming and describing ecosystem services. The importance of a standardized international classification emerged from the need to develop consistent ecosystem accounting methods and enable meaningful comparisons. Standardization was particularly essential in cases where ecosystem services were linked to economic accounting. Over time, it has become evident that, beyond environmental accounting, a systematic approach also enhances efforts to map and value ecosystem services and supports broader ecosystem assessments. (Haines-Young & Potschin-Young, 2018). This study aligned ecosystem services according to the CICES codes.

The equivalent weight coefficients were obtained based on the correction factors listed in Table 4.2, to calculate the spatial and temporal variations of ESV at the regional scale.

Table 4.2 Correction Factors Used for Revising Parameters.

Year	Yield	NPP	NDVI	Rainfall	FVC	NPP & NDVI (average)
2000	2.39	0.65	0.74	0.93	0.85	0.69
2007	1.82	0.65	0.69	1.08	0.84	0.67
2009	1.65	0.65	0.69	0.90	0.82	0.67
2012	1.72	0.69	0.63	0.60	0.75	0.66
2018	2.29	0.71	0.63	0.81	0.64	0.67
2021	1.86	0.74	0.63	0.91	0.64	0.69

Temporal crop yield data were collected from the Bangladesh Bureau of Statistics (<http://www.bbs.gov.bd/>) and rainfall data from the Bangladesh Agricultural Research Council (BARC) (<http://www.barc.gov.bd/>). To calculate the spatiotemporal NPP, Annual

Net Primary Productivity (NPP) retrieved from NASA LP DAAC USGS EROS Center (<https://lpdaac.usgs.gov/products/mod17a3hgv006/>) data was used. The NDVI and FVC were calculated using standard procedures (Sannigrahi et al., 2019; G. Xie et al., 2017). Using the correction factors, the corresponding equivalent value coefficients were adjusted for each ES for the study period as follows:

$$\begin{aligned} F_{ij} &= B_j \times F_{n1} \\ F_{ij} &= P_j \times F_{n2} \\ F_{ij} &= V_j \times F_{n3} \\ F_{ij} &= Y_j \times F_{n4} \end{aligned} \quad (3)$$

Where, F_{ij} refers to the equivalent factor per unit area for ecosystem service i of an ecosystem in region j ; B_j, P_j, V_j, Y_j refers to the spatial and temporal regulation factor of biomass, precipitation, FVC and crop yield correction factors for region j . $F_{n1}, F_{n2}, F_{n3}, F_{n4}$ is the equivalent class of CICES code (2.2.6.2, 2.2.6.1, 2.2.1.3, 2.2.1.4, 2.1.1.1, 2.2.2.2, 2.2.2.3, 1.1.1.2, 1.2.1.2, 3.1.1.1, 3.1.1.2, 3.1.2.4), (4.2.1.2, 2.2.5.1), (2.2.1.1, 2.2.4.1) and (1.1.1.1). The estimation of the correction factors B_j, P_j, V_j and Y_j for the full region and administrative levels reflects the following pattern of NPP, biomass, NDVI, and rainfall at the study region and throughout the entire country as follows:

$$\begin{aligned} B_i &= \left(\frac{NDVI_i}{NDVI_j} + \frac{NPP_i}{NPP_j} \right) \\ P_i &= \left(\frac{R_i}{R_j} \right) \\ V_i &= \left(\frac{FVC_i}{FVC_j} \right) \\ Y_i &= \left(\frac{Y_i}{Y_j} \right) \end{aligned} \quad (4)$$

Where R and Y are rainfall and crop yield factors, i, j are the distribution of the factors at the study region and country scale. F_{n1}, F_{n2}, F_{n3} , and F_{n4} are listed in (Table 4).

Table 4.3 Equivalent ecosystems service and their corresponding CICES code in the study area.

Ecosystem services	Class	CICES Code
Provisioning	Surface water used as a material	4.2.1.2
	Cultivated terrestrial plants grown for nutritional purposes	1.1.1.1
	Fibers and other materials from cultivated plants, fungi, algae, and bacteria for direct use or processing	1.1.1.2
	Higher plants are used to breed new strains or varieties	1.2.1.2
Regulating and Maintenance	Regulation of temperature and humidity, including ventilation and transpiration	2.2.6.2
	Regulation of chemical composition of atmosphere and oceans	2.2.6.1
	Hydrological cycle Including flood control, and Wind protection	2.2.1.3, 2.2.1.4
	Regulation of the chemical condition of freshwaters by living processes	2.2.5.1
	Control of erosion rates	2.2.1.1
	Bioremediation by micro-organisms, algae, plants, and animals	2.1.1.1
	Pest and disease control	2.2.3.1, 2.2.3.2
	Weathering processes and their effect on soil quality	2.2.4.1
	Mineral substances used for nutritional purposes	4.3.1.1
	Seed dispersal	2.2.2.2
Cultural	Maintaining nursery populations and habitats including gene pool protection	2.2.2.3
	Characteristics of living systems that enable activities promoting health, recuperation, or enjoyment through active, passive, or immersive interactions)	3.1.1.1, 3.1.1.2
	Characteristics of living systems that enable aesthetic experiences	3.1.2.4

4.2.3.4 Calculating Regional Ecosystem Services

Ecosystem services (ES) are controlled by many ecological processes, which are intimately tied to regional ecological characteristics (G. Xie et al., 2017). The ESV of five ecosystems in Dhaka for six reference years was measured using these updated unit values and calculated the spatiotemporal distribution and changes of ESV. The total ESV was calculated as follows:

$$ESV_K = \sum_{f=1}^{17} (A_K \times F_{ij}) \quad (5)$$

$$ESV_f = \sum_k^5 (A_K \times F_{ij}) \quad (6)$$

$$ESV = \sum_{f=1}^{17} \sum_{k=1}^5 (A_k \times F_{ij}) \quad (7)$$

Where, ESV_K , ESV_f , and ESV is the ecosystem service value ($\text{US\$ } ha^{-1}yr^{-1}$) of ecosystem type k , and ecosystem service f , total ecosystem service value, F_{ij} is the updated equivalent value coefficient of ecosystem service f and ecosystem types k , A_K is the area (ha) of ecosystem type k (Costanza et al., 2014; Makwinja et al., 2021). The ESV change rate (ESV_{cr}) through the study period was calculated by using this equation (XIE Gao-di, 2008).

$$ESV_{cr} = \frac{ESV_{end} - ESV_{start}}{ESV_{start}} \times 100\% \quad (8)$$

4.2.3.5 Trade-offs between Ecosystem Services Bundles

The relationships between ES (provisioning vs. regulating; regulating vs. cultural; provisioning vs. cultural) were analyzed in different LULC classes Using simple linear regression models. ESV from all CICES classes were aggregated by year and land use class into their respective categories (provisioning, regulating, or cultural). The aggregated ESV values were normalized within each land use class, scaling them from ESV in million dollars to a $[0 \sim 1]$ range. Simple linear regression models were then fitted separately for each land use class. The analysis was conducted in *R* version 4.3, and scatter plots and model fits were visualized using the *ggplot2* plotting library.

4.2.3.6 Ecosystem Sensitivity Analysis

A sensitivity analysis was carried out to assess the results' reliability. Sensitivity tests were carried out to assess the percentage change in ESV for a given percentage change in the value coefficient since there are uncertainties in the value coefficients and because LULC types and ecosystems are not always exact fits (S. Liu et al., 2010). Therefore, sensitivity analysis was performed to test the robustness of the probability setting and assessment results in this study. This study calculated the coefficient of sensitivity (CS) based on the concept of elasticity in economics (Kreuter et al., 2001).

$$CS = \frac{\frac{ESV_j - ESV_i}{ESV_i}}{\frac{VC_{jk} - VC_{ik}}{VC_{ik}}} \quad (9)$$

Where ESV is the estimated ecosystem services value, VC is the value coefficients, i and j are the initial and adjusted values. K is the land cover type. If CS is more than one, the estimated ecosystem value is elastic to that coefficient; however, if CS is less than one, the estimated ecosystem value is inelastic, and the result will be reliable. In this study, the percentage change of the probability for each scenario was set as a $\pm 50\%$ adjustment (Hasan et al., 2020).

4.3 Results and Discussion

4.3.1 Ecosystem Services Class Using the Common International Classification (CICES v5.1)

The Common International Classification of Ecosystem Services (CICES) was designed to facilitate the measurement, accounting, and assessment of ecosystem services. Although it was initially developed as part of the United Nations Statistical Division's (UNSD) System of Environmental and Economic Accounting (SEEA), it has gained widespread use in ecosystem services research for creating indicators, mapping, and valuation. The concept of a standardized international classification emerged from the need to develop ecosystem accounting methods and enable comparisons, necessitating a uniform description of ecosystem services. This standardization is essential for its integration with economic accounting. Since its introduction, interest in CICES has grown significantly. It has become clear that systematic approaches to naming and describing ecosystem services benefit not only environmental accounting but also the broader tasks of mapping and valuing ecosystem services and conducting ecosystem assessments. Since 2018, CICES has been cited in over 1000 scientific papers, many of which have provided detailed feedback on its structure and scope (Haines-Young & Potschin-Young, 2018).

In this study, land use and land cover (LULC) classification was based on the CICES framework. The ecosystem service classes were aligned globally, and their values were adjusted using regional correction factors. This method led to the development of region-specific standard coefficients for ecosystem service values in the study area.

Table 4.4 Equivalent ecosystems (LULC) and coefficients value at 2021 (US\$ $ha^{-1}yr^{-1}$) for ecosystem services values (ESV) per unit area with their respective CICES code (Costanza et al., 1997, 2014; de Groot et al., 2012; Sannigrahi et al., 2019; XIE Gao-di, 2008).

ES	Class	CICES Code	WB	V	AL	BL	BU
Provisioning	Surface water used as a material (SF)	4.2.1.2	7244.63	441.97	0	0	0
	Cultivated terrestrial plants grown for nutritional purposes (CTPN)	1.1.1.1	930.46	258.46	238.73	0	0
	Fibers and other materials from cultivated plants, fungi, algae, and bacteria for direct use or processing (FMO)	1.1.1.2	549.23	108.55	93.1	0	0
	Higher plants are used to breed new strains or varieties (HPNS)	1.2.1.2	1509.41	29.72	0	0	0
Regulating and Maintenance	Regulation of temperature and humidity, including ventilation and transpiration (RTHVT)	2.2.6.2	0	18.60	171.89	0.08	0
	Regulation of chemical composition of atmosphere and oceans (RCCAO)	2.2.6.1	630.64	2641.46	231.57	0	46.52
	Hydrological cycle Including flood control, and Wind protection (HCFWC)	2.2.1.3, 2.2.1.4	3858.8	85.29	0	0	0
	Regulation of the chemical condition of freshwater by living processes (RCCFLP)	2.2.5.1	2863.73	34.89	183.82	0	0
	Control of erosion rates (CER)	2.2.1.1	3369.02	19.38	0	0	0
	Bioremediation by micro-organisms, algae, plants, and animals (BMOAPA)	2.1.1.1	4137.94	7.75	331.84	0	0
	Pest and disease control (PAD)	2.2.3.1, 2.2.3.2	1225.1	14.22	243.51	0	0
	Weathering processes and their effect on soil quality (WPSQ)	2.2.4.1	0	4.66	350.94	0	0
	Mineral substances used for nutritional purposes (MSNP)	4.3.1.1	2213.71	3.88	0	0	0
	Seed dispersal (SD)	2.2.2.2	0	38.77	0	0	0
	Maintaining nursery	2.2.2.3	454.50	0	0	0	0

	populations and habitats including gene pool protection (MNPH)						
Cultural	Characteristics of living systems that enable activities promoting health, recuperation, or enjoyment through active, passive, or immersive interactions (PHRAPI)	3.1.1.1, 3.1.1.2	5656.39	1120.42	0	0	0
	Characteristics of living systems that enable aesthetic experiences (CLSAE)	3.1.2.4	1669.65	5.07	0	0	290.77

WB=Waterbody, V=Vegetation cover, AL= Agricultural land, BL=Bare land, BU= Built-up area.

4.3.2 Ecosystem Service Value of Dhaka City

Regional ecosystem services values were calculated by applying the developed regional coefficient values and LULC classification area.

Table 4.5 Temporal ecosystem service value of the study area

		Ecosystem service value ($\times 10^6$ USD)					
Ecosystem Services	CICES Code	2000	2007	2009	2012	2018	2021
Provisioning	4.2.1.2	44.74	17.66	32.25	17.14	14.24	13.84
	1.1.1.1	21.94	12.71	10.63	8.61	7.84	5.46
	1.1.1.2	6.76	4.91	4.55	3.53	2.38	2.11
	1.2.1.2	14.19	9.96	9.55	7.61	4.69	4.21
Regulating and Maintenance	2.2.6.2	1.55	2.76	2.46	1.96	1.42	1.29
	2.2.6.1	31.23	24.86	22.01	15.22	12.72	10.72
	2.2.1.3, 2.2.1.4	36.37	25.54	24.46	19.50	12.03	10.78
	2.2.5.1	18.89	40.25	12.80	6.87	5.75	5.65
	2.2.1.1	19.12	13.73	12.96	9.55	4.93	4.30
	2.1.1.1	40.95	28.91	27.40	21.95	13.83	12.49
	2.2.3.1, 2.2.3.2	13.40	9.57	8.92	7.14	4.67	4.23
	2.2.4.1	1.76	1.42	0.02	0.83	0.62	0.57
	4.3.1.1	20.47	14.33	13.76	11.01	6.75	6.07
	2.2.2.2	0.34	0.43	0.37	0.25	0.22	0.19
	2.2.2.3	4.20	2.94	2.82	2.26	1.38	1.24
	3.1.1.1, 3.1.1.2	61.94	44.46	41.97	32.45	21.03	18.44
	3.1.2.4	19.34	14.98	14.78	13.85	11.06	12.08

4.3.3 Changes in Total Ecosystem Service Value (ESV)

The ESV for Dhaka city was \$359.76 million in 2000 (2021 value of the USD) (Table 5), with about (81.32%) of this value comprised of waterbodies, vegetation cover, and agricultural land contributed 11.34% and 3.39% of this total ESV, while built-up land accounted for just 1.60% of the total area of Dhaka. Comparatively, areas of bare land reported less than 1% of the total ESV.

Table 4.6 Total ecosystem services value (ESV) in (Million USD \$) by land use type and the change in Dhaka city from 2000 to 2021.

Year	2000	2007	2009	2012	2018	2021
Waterbody	298.4660	220.1986	199.846	148.366	95.9941	86.7634
Vegetation cover	42.067877	33.95027	29.0402	17.9980	16.3633	12.5434
Agricultural Land	14.710113	10.4500	7.69936	6.95582	6.51858	5.87155
Bare Land	0.0002316	0.000528	0.00080	0.00065	0.00082	0.00058
Built-up-Area	4.521051	4.83118	5.10515	6.42290	6.91860	8.69781

The research revealed a substantial 68.34% reduction in ESV, which corresponds to \$245.88 million (in 2021 USD), over the period from 2000 to 2021. This decline primarily resulted from the transformation of water bodies (-70.93%), agricultural land (-60.08%), as well as vegetation cover (-70.18%) into urban built-up areas and other uses.

From 2000–2009, the ESV of Dhaka decreased by 32.81% or \$118.07 million (based on the 2021 value of the USD). The ESVs of vegetation cover, waterbodies, and agricultural land all declined significantly in terms of land use/cover types by \$13.02 million, \$98.61 million, and \$7.01 million, while the ESVs of bare land and built-up-areas increased by \$ 0.0005 million and \$4.17 million, respectively.

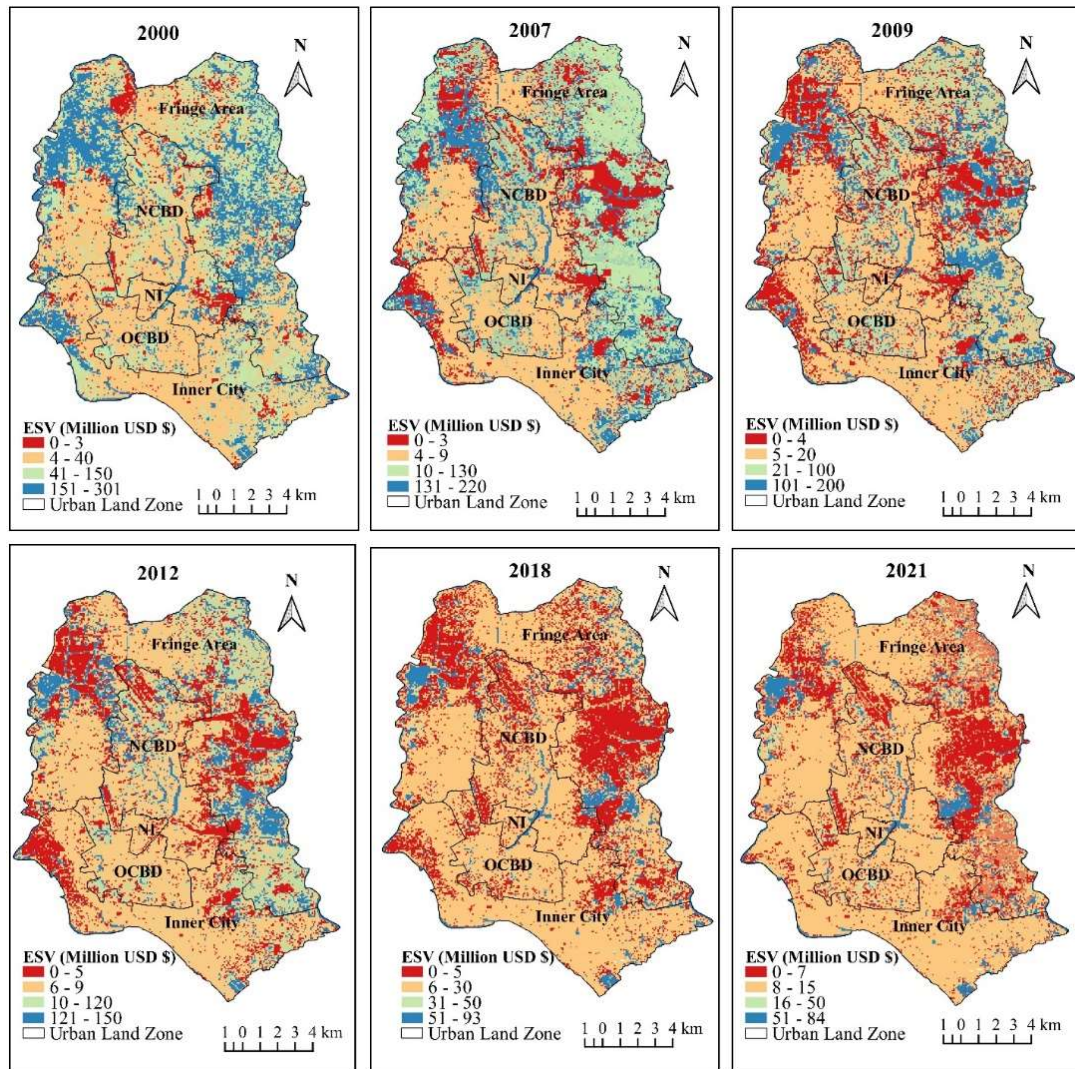


Figure 4. 2 Spatially distributed total ESV (Million USD \$) in Dhaka from 2000-2021

During the period 2009–2021, the ESV of Dhaka decreased by 63.95 %, or \$ 127.81 million (based on the 2021 value of the USD). The ESVs for waterbodies, vegetation cover, and agriculture land again decreased, by \$ 113.08 million, \$ 16.49 million, and \$1.82 million, respectively.

4.3.4 Supply and Changes in the Values of Ecosystem Service Classes in Dhaka

The study quantified and compared the contributions of each ES to the overall ESV in Dhaka. The individual contributions of each ESV were as follows, categorized by CICES codes: 3.1.1.1, 3.1.1.2 (17.02%), 2.1.1.1 (11.22%), 4.2.1.2 (10.99%), 2.2.1.3, 2.2.1.4 (9.94%), 2.2.6.1 (9.05%), 2.2.5.1 (6.97%), 3.1.2.4 (6.66%), 4.3.1.1 (5.59%), 1.1.1.1 (5.18%), 2.2.1.1 (4.99%), 1.2.1.2 (3.88%), 2.2.3.1, 2.2.3.2 (3.69%), 1.1.1.2 (1.87%), 2.2.2.3 (1.37%), 2.2.6.2 (1.00%), 2.2.4.1 (0.42%), and 2.2.2.2 (0.15%). Regulating services contributed to (53.81 %) of the total ESV, followed by cultural (23.75 %) and provisioning (22.02%). The breakdown of the total changes revealed a decline in all ES classes.

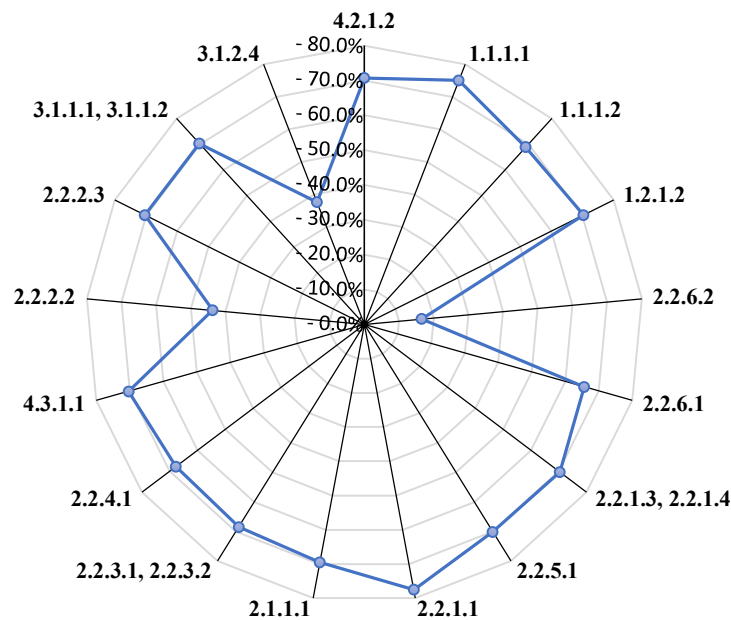
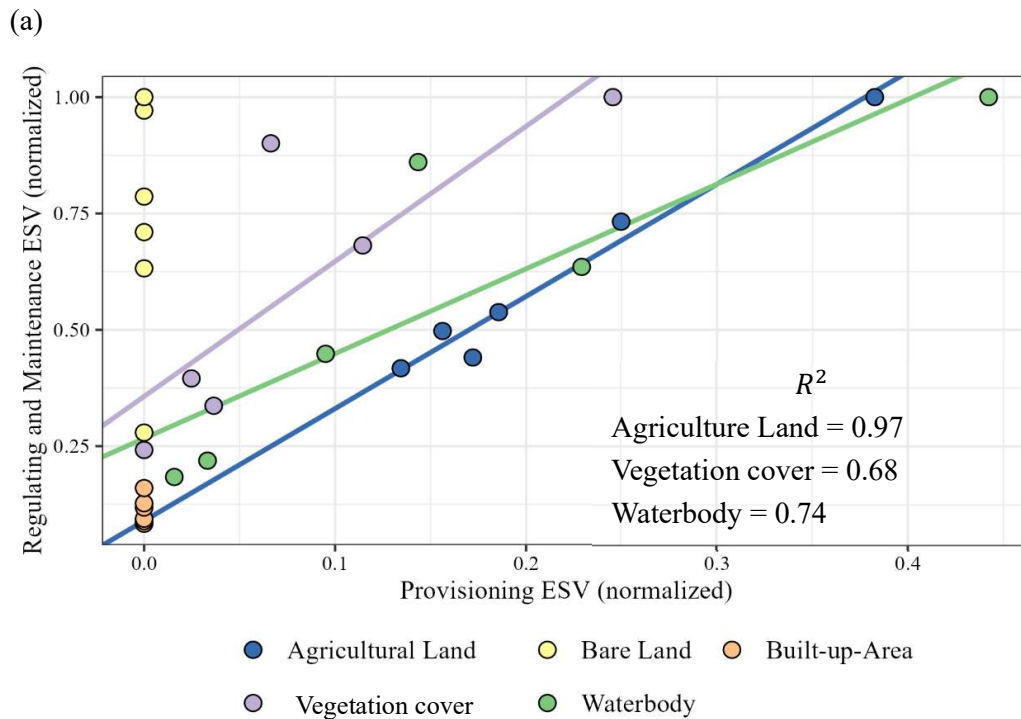


Figure 4. 3 The percentage of ESV decreases in Dhaka from 2000 to 2021

4.3.5 Trade-offs between Ecosystem Services (ES) bundles

4.3.5.1 Trade-offs between the provisioning and the regulating ES bundles

The most synergistic relationship between the provisioning and the regulating ES was observed in agricultural areas, with an R^2 (0.97), Followed by waterbody R^2 (0.74), vegetation cover R^2 (0.68) (Fig. 4.4). However, no significant evidence of trade-offs was found in bare land and built-up areas. When assessing the benefits between provisioning and regulating ES, it was found that the most significant trade-offs occurred in waterbody areas. As a result, the potential supply of regulating ES was relatively higher compared to provisioning ones in these areas. Among the provisioning ES, the CICES 4.2.1.2 class exhibited the highest ESV, while the 2.1.1.1 class held the highest value in regulating ES.



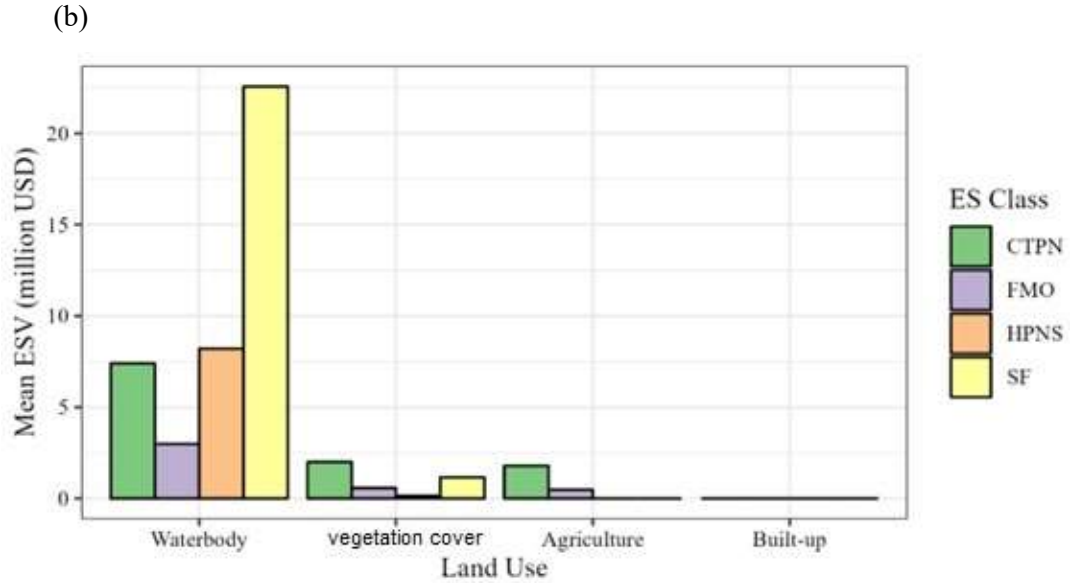
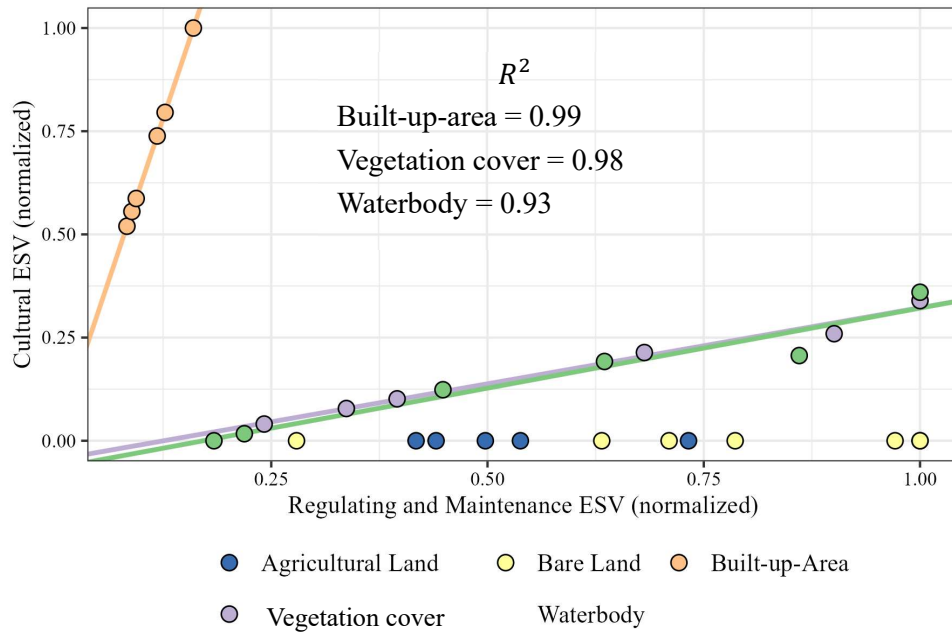


Figure 4. 4 a) Scatter plot and R^2 between provisioning and the regulating ESV by land use class. b) Supply of the provisioning ESV by land use class.

4.3.5.2 Trade-offs between regulating and cultural ES bundles

The correlation between regulating and cultural ES is illustrated in (Fig. 4.5). Among the different areas, built-up regions exhibited the highest R^2 value of 0.99 due to the aesthetic value attributed to these areas, followed by vegetation cover R^2 (0.98), and waterbody R^2 (0.93). No significant relationship was identified in bare land and agricultural land between these two types of ES. The limited potential supply of provisioning and regulating ES in bare land and built-up areas indicates that the city of Dhaka is experiencing adverse effects from urbanization. Regarding regulating ES, waterbodies contribute higher values, with CICES class 2.1.1.1 exhibiting the highest ESV.

(a)



(b)

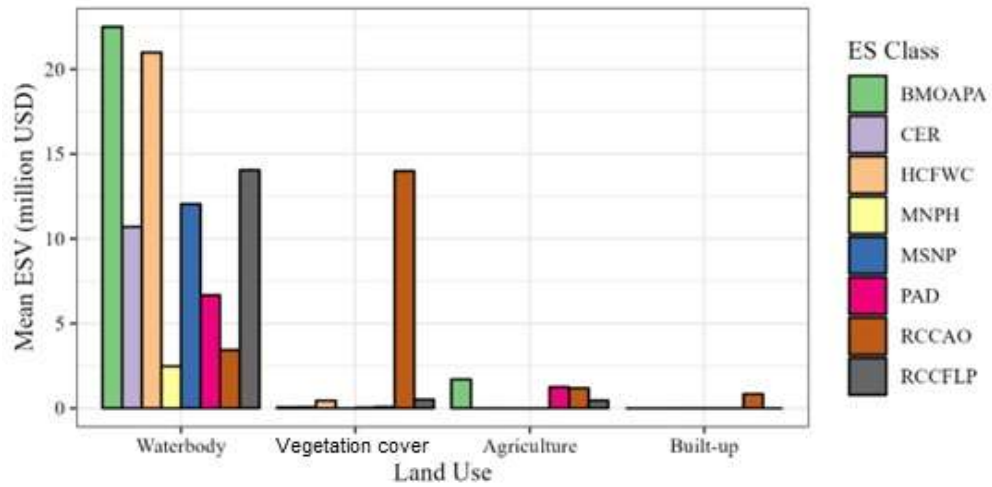
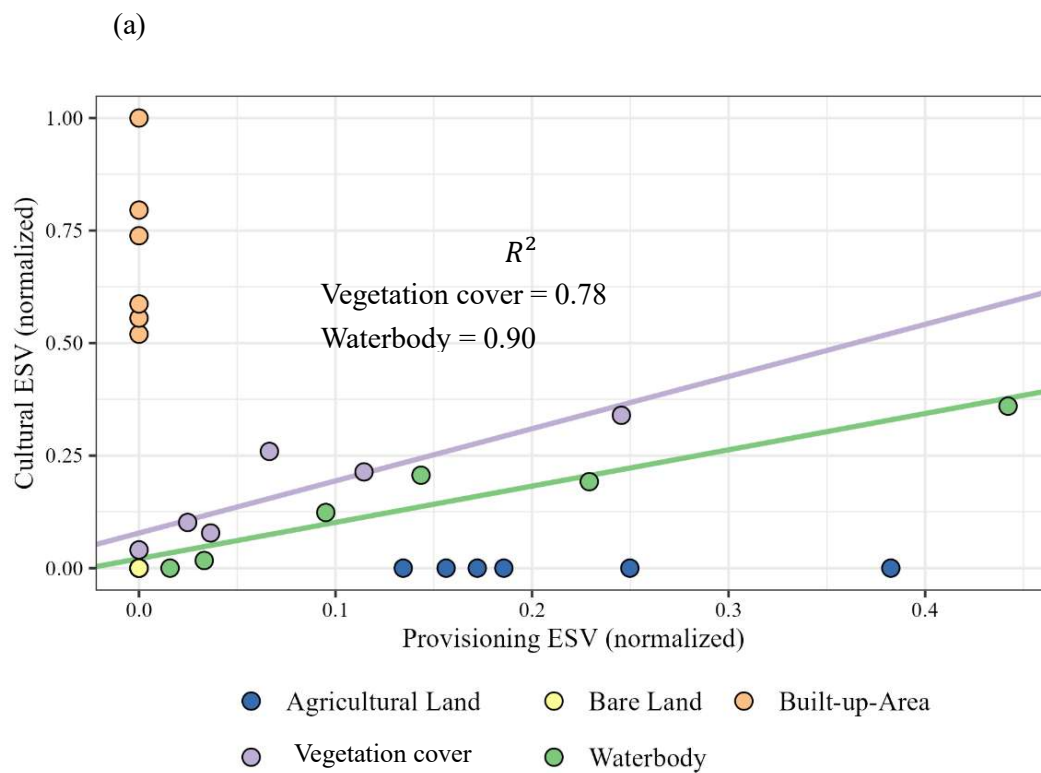


Figure 4. 5 a) Scatter plot and R^2 between the regulating and cultural ESV by land use class. b) Supply of the regulating ESV by land use class.

4.3.5.3 Trade-offs between provisioning and cultural ES bundles

The correlation between provisioning and cultural ES is illustrated in (Fig. 4.6). The strongest relationship was found in water body areas, demonstrating R^2 (0.90), followed by vegetation cover R^2 (0.78). However, no significant relationship was identified in bare land areas. Most cultural services originated from recreational and aesthetic values in waterbody, vegetation cover areas. The CICES 3.1.1.1 and 3.1.1.2 classes contribute to the highest ESV among the cultural service categories.



(b)

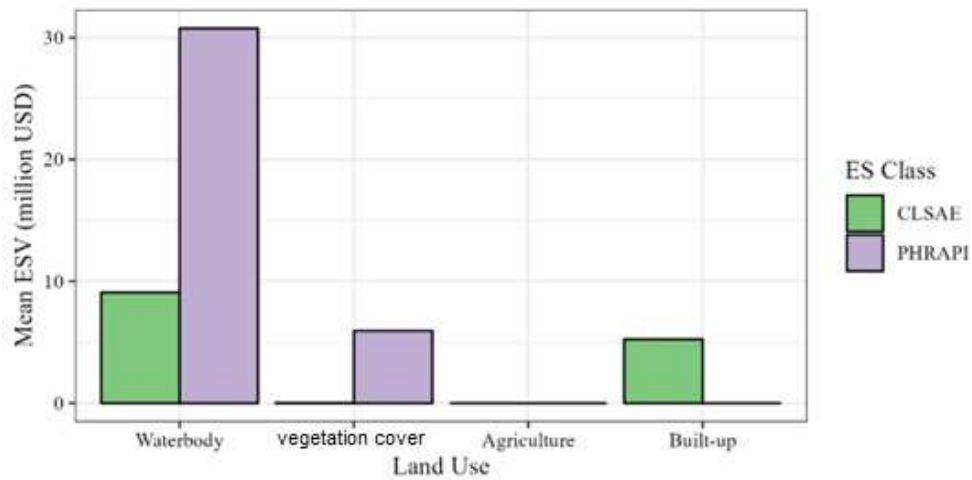


Figure 4. 6 (a) Scatter plot and R^2 between Provisioning and cultural ESV by land use class.

b) Supply of the cultural ESV by land use class.

4.4 Ecosystem Services Sensitivity Analysis

The overall ES values assessed in the study area were found to be inelastic concerning the adjusted ecosystem value coefficients, as indicated by the coefficient of sensitivity (CS) being less than one in every case (Table 4.7). The CS for waterbodies and vegetation cover was relatively high. Waterbodies had the highest coefficient of sensitivity, ranging from 0.76 to 0.83, due to their high coefficient value and large area. In comparison to waterbodies, the CS for agricultural land was lower, ranging from 0.03 to 0.05.

Table 4.7 Percentage change of the total ESV values and sensitivity coefficient (CS) after a $\pm 50\%$ adjustment of value coefficients (VC) for each land use/land cover type in Dhaka City (2000–2021)

Change in value coefficient	2000		2007		2009		2012		2018		2021	
	$\pm \%$	CS	$\pm \%$	CS	$\pm \%$	CS	$\pm \%$	CS	$\pm \%$	CS	$\pm \%$	CS
Waterbody	41.53	0.83	40.89	0.82	0.41	0.83	41.30	0.83	38.16	0.76	37.80	0.76
Vegetation cover	5.77	0.12	6.27	0.13	0.06	0.12	4.98	0.10	6.40	0.13	5.99	0.12
Built-up area	0.61	0.01	0.89	0.02	0.01	0.02	1.78	0.04	2.82	0.06	3.94	0.08
Agricultural land	2.05	0.04	1.94	0.04	0.02	0.03	1.93	0.04	2.60	0.05	2.25	0.05
Bare land	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The lower CS value for barren land indicates that changes in their value coefficient did not significantly affect the assessment of total ESV. However, the sensitivity analysis showed that the ESV estimation was robust despite uncertainties in the modified value coefficients.

4.5 Conclusion

This study developed regional coefficient values for ecosystem services analysis in Dhaka city and expanded the research scope to include their trade-offs. Based on the importance of ecological functions and their trade-offs, a spatial management framework for managing ecosystem functions was constructed. The research revealed that the conversion of waterbodies to other land classes was the highest, significantly impacting regulating services. This research integrated the CICES code for ecosystem service value assessment that could be a benchmark for Dhaka city ecosystem service analysis and can contribute to the global TEEB (The Economics of Ecosystem & Biodiversity) database. In addition, the findings of this research can be used for ecosystem planning and management.

Chapter 5

Investigating the Spatiotemporal Patterns of the Degree of Urbanization and its Relationship with Ecosystem Service Values

5.1 Introduction

Urbanization represents one of the most significant social transformations of the contemporary era, involving various economic, social, physical, and environmental processes (Cord et al., 2017). In the 21st century, urban areas, including Dhaka, are increasingly facing challenges from natural and human-induced crises, such as flooding, air pollution, and the urban heat island effect. To enhance urban resilience against these threats, the development of urban risk assessment maps and suitable land-use profiles is essential (UN-Habitat, 2024). In the present day, more than half of the global population resides in urban areas, a figure that is rapidly growing, thus making urbanization a critical global priority (United Nations, 2019).

To control urban sprawl, rapidly expanding cities are improving land use efficiency by increasing building heights (Galster et al., 2001). This trend is particularly prevalent in densely populated Asian countries, where many middle- and high-rise buildings are constructed (Frolking et al., 2013). Vertical expansion is crucial for economically advanced metropolises and large, space-constrained cities like Dhaka. Traditionally, building heights were determined using maps showing the floor-area ratio (Kushol et al., 2013), Statistical yearbooks (BBS, 2022), aerial photos, and local agency-supplied maps (Maksud Kamal & Midorikawa, 2004). Recently, digital building height models (DBHs) generated from remote sensing techniques have become popular for monitoring urban vertical growth (Misra et al., 2018). These urban growth data have various applications, such as modeling urban expansion, reconstructing buildings, and observing heat islands.

The increasing availability of Earth observation (EO) data has provided a critical tool for examining the built environment both horizontally and vertically (C. Yang & Zhao, 2022). Over the past two decades, there has been a growing body of literature devoted to the characterization of urban vertical profiles (Gamba & Houshmand, 2000; X. Liu et

al.,2024; Misra et al., 2018; C. Yang & Zhao, 2022). Key Earth Observation (EO) data sources, such as TerraSAR-X Add-on for Digital Elevation Measurements (TanDEM-X DSM), Shuttle Radar Topography Mission (SRTM), and Advanced Land Observing Satellite (ALOS), effectively balance high spatial resolution with global coverage, capturing vertical features in urban environments. Urbanization is quantified using the technomass indicator, which incorporates human-made material stocks in buildings and infrastructure (Inostroza et al., 2019).

Previous research has primarily focused on the impact of urbanization on vegetation cover, land surface temperature (LST), vertical growth assessment, and urban area expansion (Lin et al., 2014; F. Rahman & Rahman, 2023; W. Zhang et al., 2017). For instance, studies on Dhaka have explored the effects of spatial growth on LST (Rahman et al., 2020) and development zoning (Rahman et al., 2021) using Digital Elevation Model (DEM) images. Nevertheless, a comprehensive understanding of the vertical profiles of urban growth and coupling with the degree of urbanization and their relationship with ESV remains limited.

To address these gaps, Dhaka, one of the world's most populous cities, was selected as the study area. Using multi-source data such as DEM imagery, satellite-derived biophysical indices, population density (PD), and nighttime light (NTL) intensity from 2000 to 2021, the study aims to obtain high-precision data on built-up area boundaries, building footprints, and height information. The specific objectives of this study are:

1. To monitor and assess the spatiotemporal vertical profiles of Dhaka City.
2. To calculate and analyze the degree of urbanization in the city.
3. To map and analyze urbanization indicators.
4. To evaluate the spatiotemporal degree of urbanization and its relationship with ESV

Overall, this study seeks to deepen understanding of urbanization's impact on landscape patterns, providing essential information for identifying potential ecological effects and guiding urban planning.

5.2 Materials and Methods

5.2.1 Study Area

Since Bangladesh's liberation, Dhaka has accommodated a substantial portion of the country's urban population. The city's inner core exhibits a trend towards high-density development due to the proximity between residential and commercial areas (Islam et al., 2009). The increasing demands of business activities, ease of accessibility, and inadequate land use zoning have led to the construction of commercial buildings along major road networks and in Central Business Districts (CBDs) (Mohsin, 1989). In the early 20th century, private investments and new access to bank loans prompted the development of high-rise shopping complexes (Islam & Adnan, 2011).

Additionally, uncontrolled development in fringe areas has resulted in the loss of valuable agricultural land, wetlands, floodplains, and other ecologically critical areas. The alarming reduction of wetlands in Dhaka has been documented in recent research (H. M. Abdullah et al., 2024).

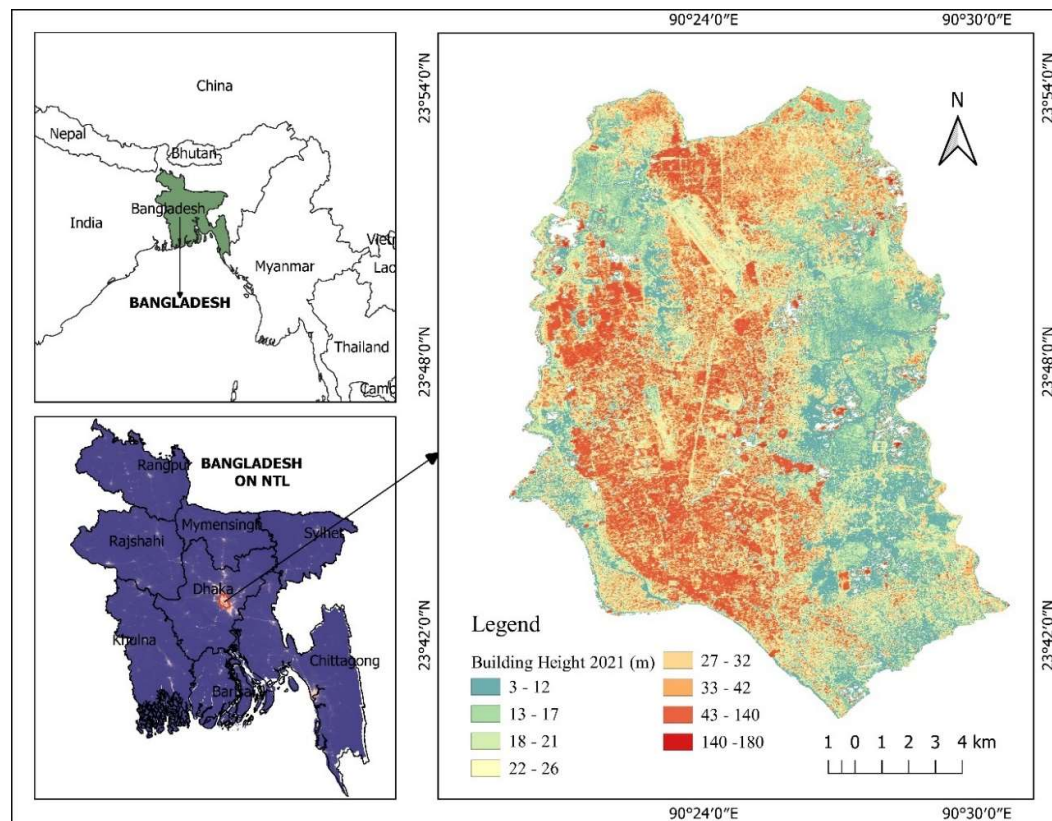


Figure 5. 1 Built-up class on TanDEM image

5.2.2 Datasets

Vertical urban growth is one of the important indicators for analyzing the urbanization pattern in rapidly urbanizing cities. The data utilized in this research can be categorized into the following: (1) reference building height, (2) DEM imageries, (3) biophysical indices extracted from multispectral (MS) imageries, (4) impervious surface data, (5) population density (PD), and (6) Visible Infrared Suite Day/Night Band (VIIRS DNB) nighttime composites. All explanatory factors were collected and preprocessed using the cloud-based Google Earth Engine (GEE) platform. The extracted building height data were validated with ground-based building height data. Building height was extracted by generating nDSM. The elevational difference between the digital surface model (DSM) and digital terrain model (DTM) was used to calculate the nDSM. In this study, a multi-directional processing and slope-dependent filtering technique called “MSD filters” was used for DTM generation (Misra et al., 2018). Parameters such as the Gaussian smoothing kernel size (100 m), the scan line filter extent (100 m), the height threshold (3 m), and the slope threshold (300) were used to segregate the ground and non-ground pixels. SRTM, AW3D30M and VIIRS-DNB data were downsampled to $12\text{ m} \times 12\text{ m}$ pixel size by preserving the same spectral resolution before image classification. The re-scaled SRTM, AW3D30M, and VIIRS-DNB data match well with other remote sensing data, such as ALOS PALSAR and TanDEM-X DSM (Md. M. Rahman et al., 2020) for temporal vertical growth analysis of Dhaka city.

To reduce the influence of vertical objects other than buildings, such as vegetation cover, data was processed and validated with the Landsat images. The technical workflow of data preprocessing is depicted in Fig. 4.2, and the datasets are summarized in Table 4.1.

Table 5.1 Datasets used in this study.

Data	Resolution	Sources	Acquisition Date
Landsat 5,8	30m	https://earthexplorer.usgs.gov/	2000,2007,2009, 2012,2018,2021
SRTM	30m	https://earthexplorer.usgs.gov/scene/metadata/full/5e83a3ee1af480c5/SRTMIN23E090V3/	2000
ALOS PALSAR	12.5m	https://search.asf.alaska.edu/#/?dataset=ALOS	2007
AW3D30M	30m	https://www.eorc.jaxa.jp/ALOS/en/dataset/aw3d30/aw3d30_e.htm	2009
TanDEM-X	12m	https://eoweb.dlr.de/egp/docs/user/downloading_ordered_data.html#	2012, 2018,2021
VIIRS-DNB	464 m	https://eogdata.mines.edu/products/vnl/#monthly	2021
An extended time series nighttime light data	464 m	Z. Chen et al., 2021	(2000–2020)
Ground-Based Building and Land Use Zoning Data	-	http://rajuk.portal.gov.bd/site/page/27748acb-1e72-4ea8-bfe3-0588d4e9f158	Building Data 2018 By Bangladesh Capital City Authority (RAJUK)

5.2.3 Description of the Datasets

5.2.3.1 SRTM DEM: The Shuttle Radar Topography Mission (SRTM), flown on Space Shuttle Endeavour from 11 to 22 February in 2000 was a joint project of the National Aeronautics and Space Administration (NASA), the National Geospatial-Intelligence Agency (NGA) and the German and Italian Space Agencies (L. Yang et al., 2011). Until 2014, the global dataset was available at a 3-arcsecond posting for regions outside of the US. In 2015, the LP DAAC (Land Processes Distributed Active Archive Center) released the NASA SRTM Version 3.0 Global 1-arcsecond dataset (SRTMGL1) (Earth Data, 2022). Its RMSE (root-mean-square-error) ranges from 5.9 m in urban areas to 10.4 m in bushland (Misra et al., 2018; Santillan & Makinano-Santillan, 2016). In this research, the 1-arcsecond (approximately 30 m at the equator) SRTMGL1 was used for the vertical height calculation of Dhaka city. It is available from NASA's Earth Explorer website (USGS, 2022).

5.2.3.2 ALOS PALSAR DEM: Advanced Land Observing Satellite (ALOS), also known as DAICHI, was developed to contribute to the fields of mapping, precise regional land-coverage observation, disaster monitoring, and resource surveying. ALOS was a mission of the Japan Aerospace Exploration Agency (Laurencelle, 2019). The ALOS has three remote-sensing instruments: the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) for digital elevation mapping, the Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) for precise land coverage observation, and the Phased Array type L-band Synthetic Aperture Radar (PALSAR) for day-and-night and all-weather land observation (JAXA, 2022). The high-resolution ALOS-PALSAR RTC DEM from Alaska Satellite Facility with a spatial resolution of 12.5 m is used in this study to identify and extract the vertical height analysis of the city.

5.2.3.3 AW3D30M DEM: Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) was an optical sensor onboard the Advanced Land Observing Satellite (ALOS) operated from 2006 to 2011 and was designed to generate worldwide elevation data. The sensor consists of three independent panchromatic radiometers for viewing forward, nadir, and backward in 2.5 m ground resolution (Tadono et al., 2014), which was processed with a 5 m grid spacing to generate a global elevation dataset, AW3D (Takaku et al., 2016). The AW3D DSM is commercially distributed at a 5 m resolution, while a 30 m down-sampled dataset (known as ‘AW3D30’) is publicly available. The absolute accuracy of AW3D30 data was about 1.9 ~ 2.3m RMSE for horizontal accuracy and 2.1~3.4 m RMSE for vertical accuracy (Tadono et al., 2014; Takaku et al., 2016). In this research, AW3D30 data was used which is publicly available (EORC, 2022).

5.2.3.4 TanDEM-X DSM: The TanDEM-X mission is an extension of the TerraSAR-X radar mission. It is based on two TerraSAR-X radar satellites flying in close formation and equipped with a synthetic aperture radar operating at X-band to generate World DEM developed by the German Aerospace Center (DLR) (Wessel et al., 2018). The corresponding pairs of images were acquired by the twin satellites TerraSAR-X and TanDEM-X, which fly in a close helix formation with distances between 300 and 500 m of each other. The height information was derived by applying single-pass Synthetic Aperture Radar (SAR) interferometry (Krieger et al., 2007). The researcher found TanDEM-X DSM

is very effective for vertical height measurement of the city (Geiss et al., 2015; Md. M. Rahman et al., 2021). The TanDEM-X DSM data was used in this study for analyzing the vertical growth of Dhaka city for the years 2012 and 2021.

5.2.3.5 Ground-Based Data: Ground-based building data was collected from the Capital City Development Authority (RAJUK), Dhaka, Bangladesh. This building data was extracted by RAJUK under the DAP project for the Dhaka Metropolitan Development Plan (DMDP) in 2018 (Capital city authority, Dhaka, Bangladesh, 2018). Under this Detailed Area Planning (DAP) a detailed physical features survey (buildings, roads, water bodies, utilities, urban spaces, etc., with attributes) and socio-economic surveys were conducted to understand the urbanization scenario of the city (DAP, 2016-2035). Researchers used this data to analyze the effect of urban growth on land surface temperature and review the existing land use zoning (Rahman et al., 2020, 2021). In this research, this data is used for analyzing the chronological vertical development of the study area and integrating this vertical height with ecosystem service values.

5.2.3.6 Multi-temporal datasets of VIIRS-DNB nighttime light: Monthly average radiance composite images using nighttime data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) are used in this research to identify the temporal changes of urbanization. This dataset is downloaded and analyzed in the Google Earth Engine platform (Earth Engine Data Catalog, 2012), and is suitable for detecting urbanization (K. Li & Chen, 2018) which is one of the key factors to evaluate the ecosystem service values (Wan et al., 2015). Among various remote sensing images, the night-time light images from VIIRS-DNB can detect artificial lights from cities, towns, industrial sites, and other human activities at night (Baugh et al., 2013; Elvidge et al., 2013). From the establishment of the Defense Meteorological Program-Operational Line-Scan System (DMSP-OLS), archive (1992), and VIIRS – DNB data to date, researchers have been widely used in the fields of urban studies, economics, sociology, environmental studies (C. He et al., 2006; Ma et al., 2012; Tan et al., 2018).

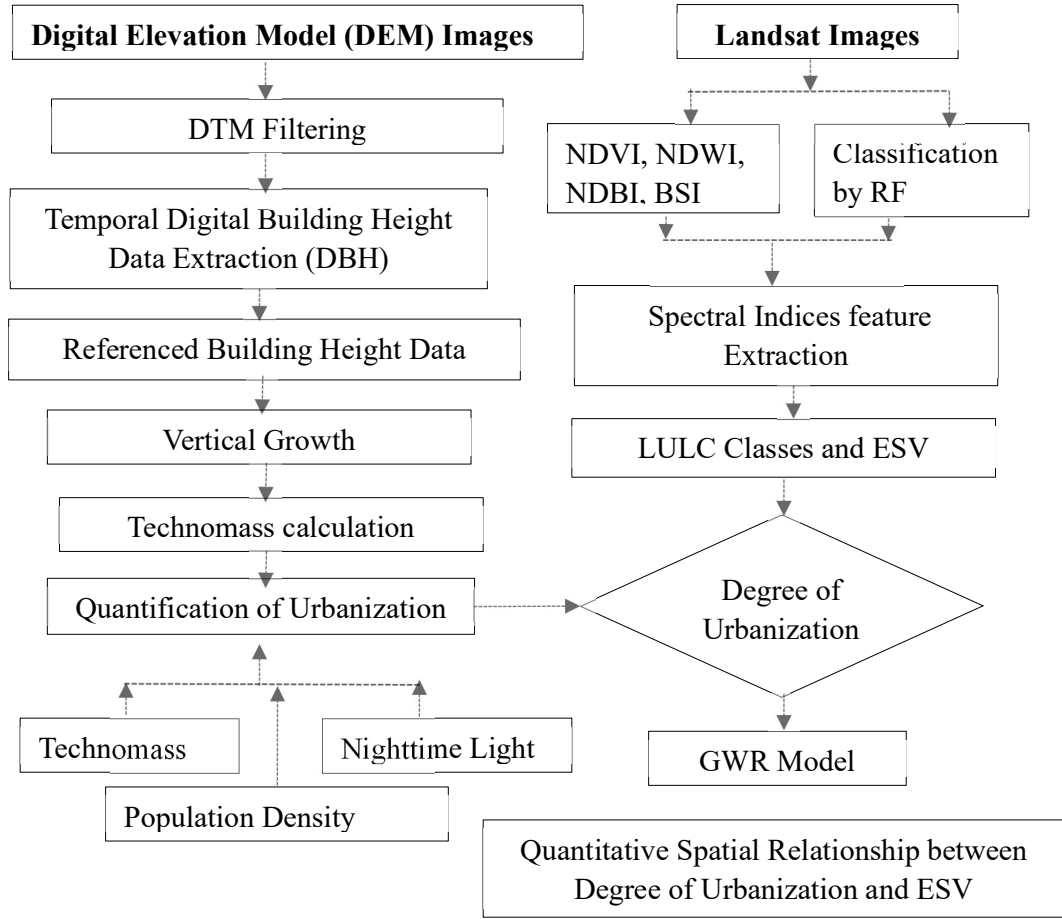


Figure 5. 2 Workflow of the study

5.2.4 Technomass Calculation to Quantify the Degree of Urbanization

Degree of urbanization quantified based on spatially explicit indicator technomass. Technomass is a three-dimensional indicator that incorporates human-made material stocks in the form of buildings and technological infrastructure within a given area (Inostroza et al., 2019). The technomass was calculated as follows:

$$\Psi = \frac{[\sum_{i=1}^n (b * h)_i + \frac{1}{2} \sum_{j=1}^n (r_j)]}{A} \quad (10)$$

Ψ is the technomass [m^3/ha], b is the building's area, h is the building's height, r is the sealed surfaces, and A is the total sample area.

5.3 Results and Discussion

5.3.1 Spatiotemporal Changes of Vertical Growth of the City

In 2000, buildings in Dhaka were generally low, with taller buildings concentrated close to the Motijheel region. Buildings measuring (5 to 6 m) were scattered across the OCBD area. Between 2007 and 2009, higher buildings (7.01 to 10.15 m) grew in the new CBD area and the core region, but their distribution was scattered, and the height range expanded in the middle region.

Between 2009 and 2012, a wide range of buildings ranging from (10.15 to 10.74 m) in height, as well as a small number of buildings ranging from (6.38 to 6.46 m) in height, emerged around the core area, forming a cluster centered on the Dhanmondi and Gulshan areas.

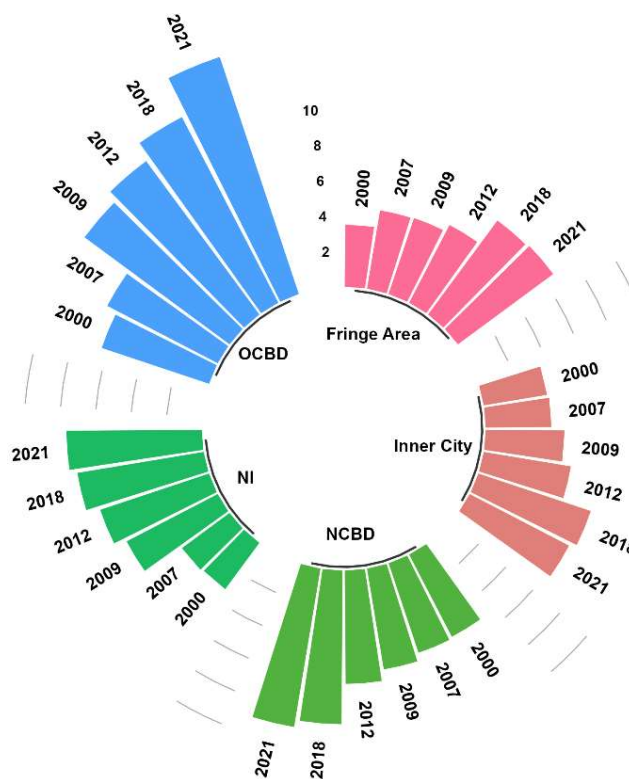


Figure 5. 3 Mean vertical growth (M) of the urban land zone in Dhaka city

Between 2012 and 2018, the number of tall buildings in the central area increased significantly, with many high-rise buildings being constructed. The area of buildings with an average height of (10.74 to 11.78 m) in the OCBD area and the northeast of the built-up

area also expanded. In the northeastern part of the built-up area, newly constructed buildings were mainly in the range of (6.58 to 8.75 m) in the fringe area.

Between 2018 and 2021, the number of buildings with an average height of (11.78 to 14.08 m) increased in the core area, while high-rise structures also increased in other regions. The maximum vertical growth was observed in the old central business district (6.37 to 14.08 m), followed by the new industrial area (3.24 to 7.62 m), newly developed CBD (5.21 to 9.04 m), rural-urban fringe area (3.50 to 6.67 m), old housing and old industrial area (3.61 to 6.30 m), respectively.

Maximum urban development is observed in the northwest and middle eastern parts of the study area. The above analysis shows that the mean building height of different zones in Dhaka changed gradually during the study period, indicating an overall upward trend. In 2000, the built-up area in the periphery was low, but it gradually increased over time. This dataset was used for technomass calculation.

5.3.2 Spatiotemporal Patterns and Changes in the Urbanization Indicators of Population Density (Pd) and Nighttime Light (NTL) Data

The mean population density of Dhaka city doubled from 11.07% to 22.20% between 2000 and 2021, with the highest increase observed in the new industrial area due to rural-to-urban migration for employment, education, and other reasons. To support the livelihood of this growing population, new settlements and housing were constructed, increasing NTL values.

For spatial analysis, zonal statistics were utilized, and it revealed that NTL values increased by 7.50% in the NCBD region, the central part of the study area, while some small declines were observed in the inner city (-1.24%) and OCBD region (-1.85%). The decrease and movement of NTL intensity in the map suggests a gradual shifting of population and economic activity. The spatiotemporal urbanization indicator showed a trend toward increasing values in the periphery. The mean value of all urbanization indicators significantly increased, and the built-up area showed a 94.94% increase during the study period (Fig. 4.4).

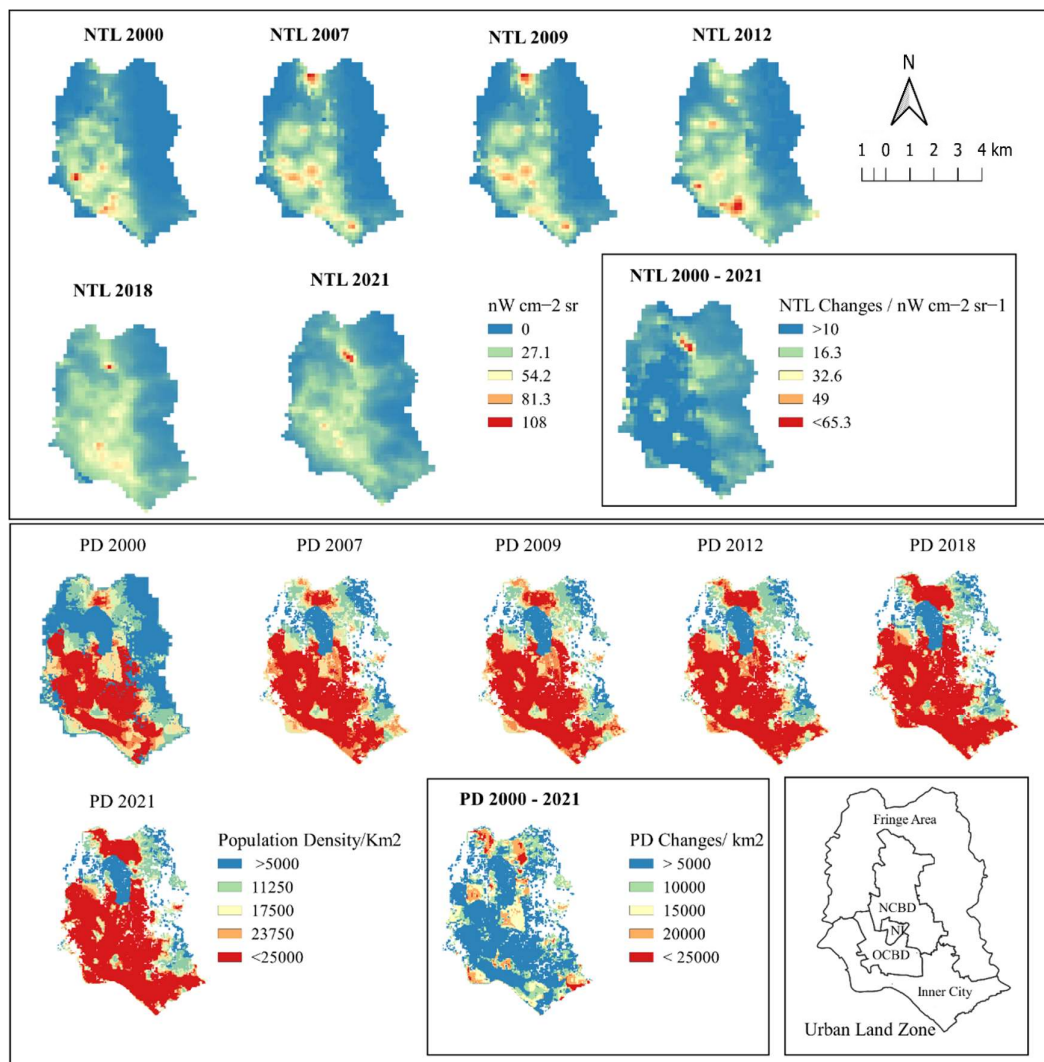


Figure 5. 4 Spatial pattern and changes of urbanization indicators.

5.3.3 Spatiotemporal Changes of Degree of Urbanization

Urbanization is reshaping landscapes globally. Urbanization was measured as an ongoing spatial process using technomass, a three-dimensional indicator that encompasses human-made material stocks such as buildings and infrastructure. The volumes and rates of technomass depict positive trends in both spatial and temporal aspects (Fig 5.5). The amounts of technomass vary significantly throughout the study area, ranging from 6,213.52 m³/ha (the lowest in 2000 in the fringe area) to 105,432.15 m³/ha (the highest in 2021 in the OCBD region). From 2000 to 2009, technomass increased by 147.64%, while the ESV decreased by 32.81%. During the period from 2009 to 2021, technomass increased by 232.38%, while the ESV decreased by 63.95%, which was double the decline observed in the 2000-2009 period.

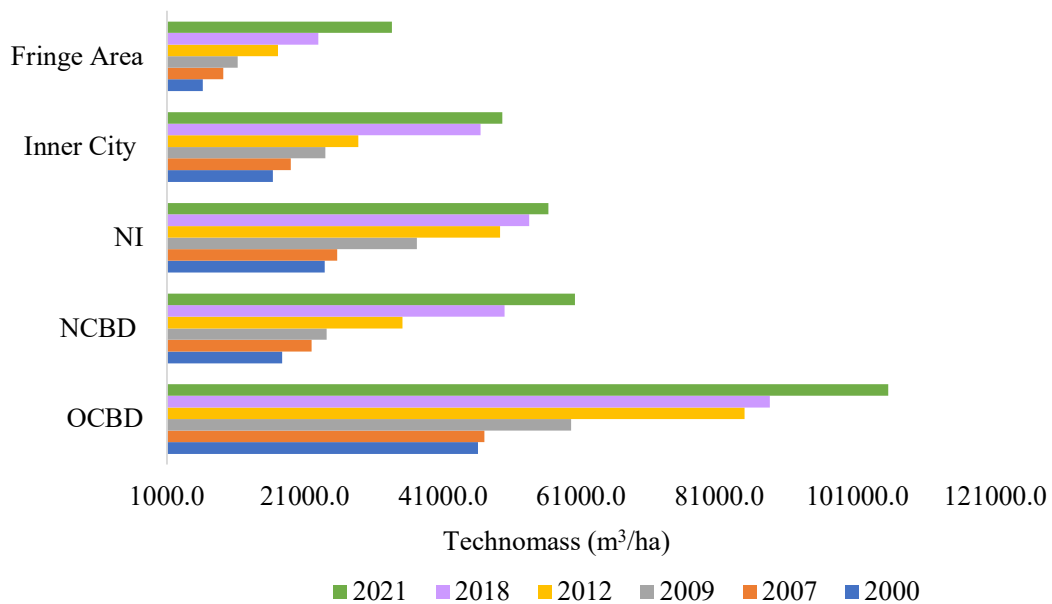


Figure 5. 5 Degree of urbanization using technomass indicator.

5.3.4 Spatial Correlation between Urbanization Indicators and ES

The GWR model is employed to analyze geographic spatial relationships between urbanization indicators and ESV changes. Local R^2 , ranging between 0 and 1, indicates that among the indicators, technomass emerged as a more appropriate indicator to analyze urbanization for ESV analysis ($r > 0.61$), followed by NTL ($r > 0.56$), and PD ($r > 0.54$) (Fig. 5.6).

The bivariate LISA map illustrates four distinct spatial correlations between ES and urbanization (Fig.5.8). High ESV -High urbanization areas are primarily concentrated in the peripheral regions, while Low ESV -High urbanization areas are distributed across the entire region and tend to cluster in the urban center. High ESV-Low urbanization areas are found in fringe areas, and Low ESV-Low urbanization areas are dispersed throughout the core areas, including water bodies and bare lands, as well as scattered across the entire region.

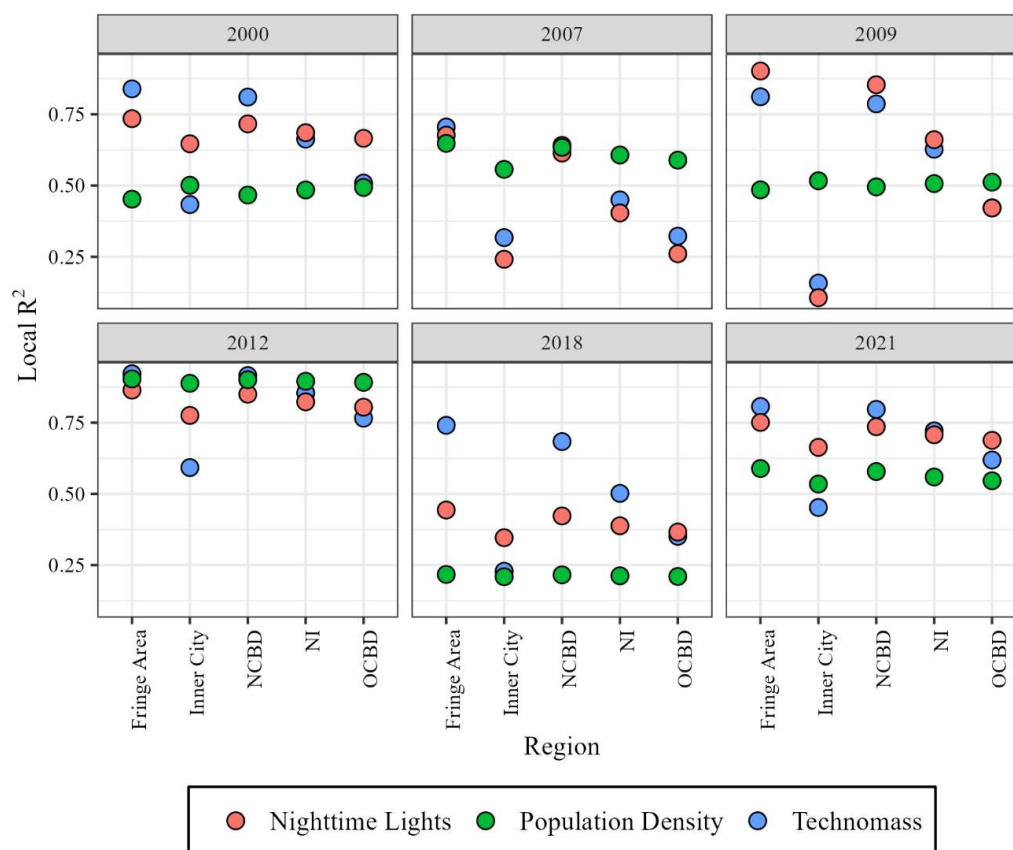


Figure 5. 6 Coefficients of GWR between urbanization indicators and ESV changes

The results of Pearson's correlation analysis revealed a significant negative correlation ($p < 0.01$) between ESV and the urbanization indicators. Technomass exhibited a strong negative association with ESV ($r > -0.96$), followed by PD ($r > -0.94$) and NTL ($r > -0.60$).

Notably, there was a significant positive correlation between technomass and NTL/PD, while the correlation between technomass/NTL/PD with ESV was negative.

Technomass proved to be a more suitable indicator for analyzing urbanization in all zones. This is primarily due to the time required for newly expanded areas to become electrified after development, as well as population movement. In the zonal statistics analysis, the urbanization trend in the rural-urban fringe area exhibited the highest positive correlation ($r > 0.90$), followed by the newly developed central business district (NCBD), inner city, OCBD, and the NI region.

5.3.5 Spatially Non-Stationary Response of ESV Changes to Degree of Urbanization

To investigate the spatial differences between urbanization levels and ESV, this research employed the GWR model. There was a negative correlation observed between changes in ESV and technomass. The coefficient of GWR revealed that the reaction of ESV changes to urbanization exhibited spatial non-stationarity.

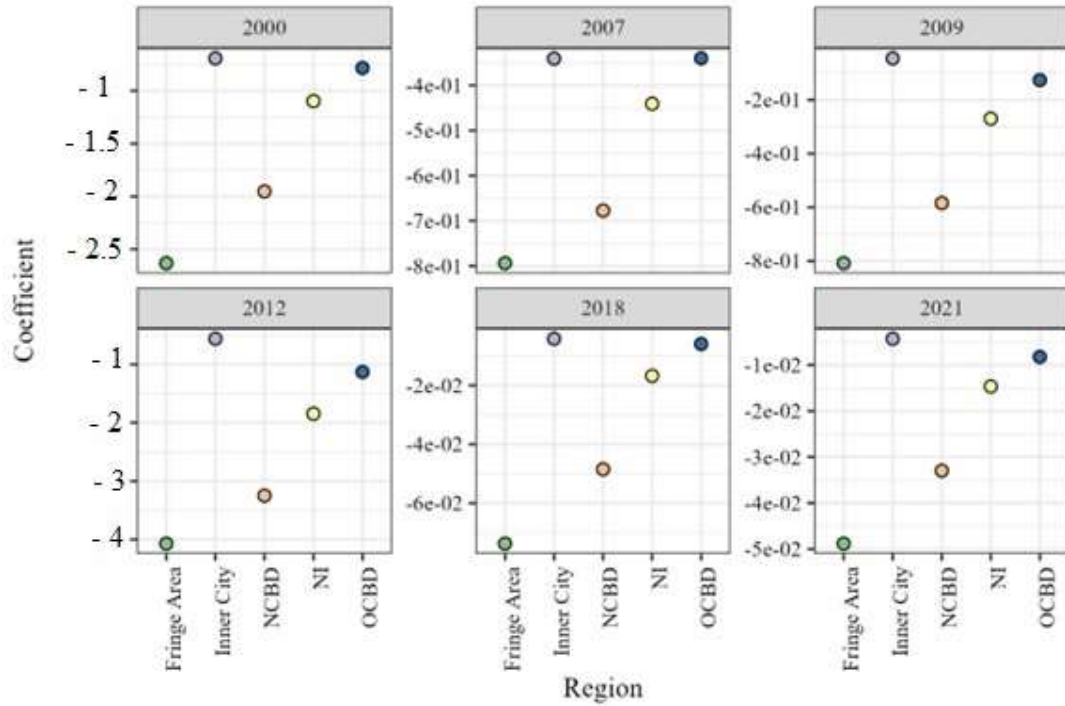


Figure 5. 7 Coefficients of GWR between the degree of urbanization and ESV changes

In Dhaka city's rural-urban fringe area, characterized by a rising trend of technomass (440.47%), there is an observation of higher rates of ESV decline (87.55%) as urbanization intensifies (Fig. 5.5). While the net ESV decreased by 68.34%, technomass increased by 243.11% throughout the study period.

5.3.6 Spatiotemporal Relationship between ESV and Urbanization

This study found a negative correlation between ES and urbanization indicators, supporting the argument for trade-offs between ES and urbanization (Tian et al., 2023). Additionally, This study revealed that the technomass indicator performed better in urbanization analysis compared to the PD and NTL indicators. The bivariate local indicators of spatial association (LISA) analysis (Fig. 5.8) revealed a large area with low ESV and high urbanization. Between 2000 and 2021, this distribution expanded to the periphery, signifying increased urbanization at the urban-rural fringe due to land availability, low prices, and insufficient land for expansion in the urban core. LISA analysis

depicted that an increase in the degree of urbanization leads to a decrease in the supply of ES (Fig. 5.8). These results support the findings regarding the impact of urban expansion on the supply-demand balance of ES (Zeng et al., 2023).

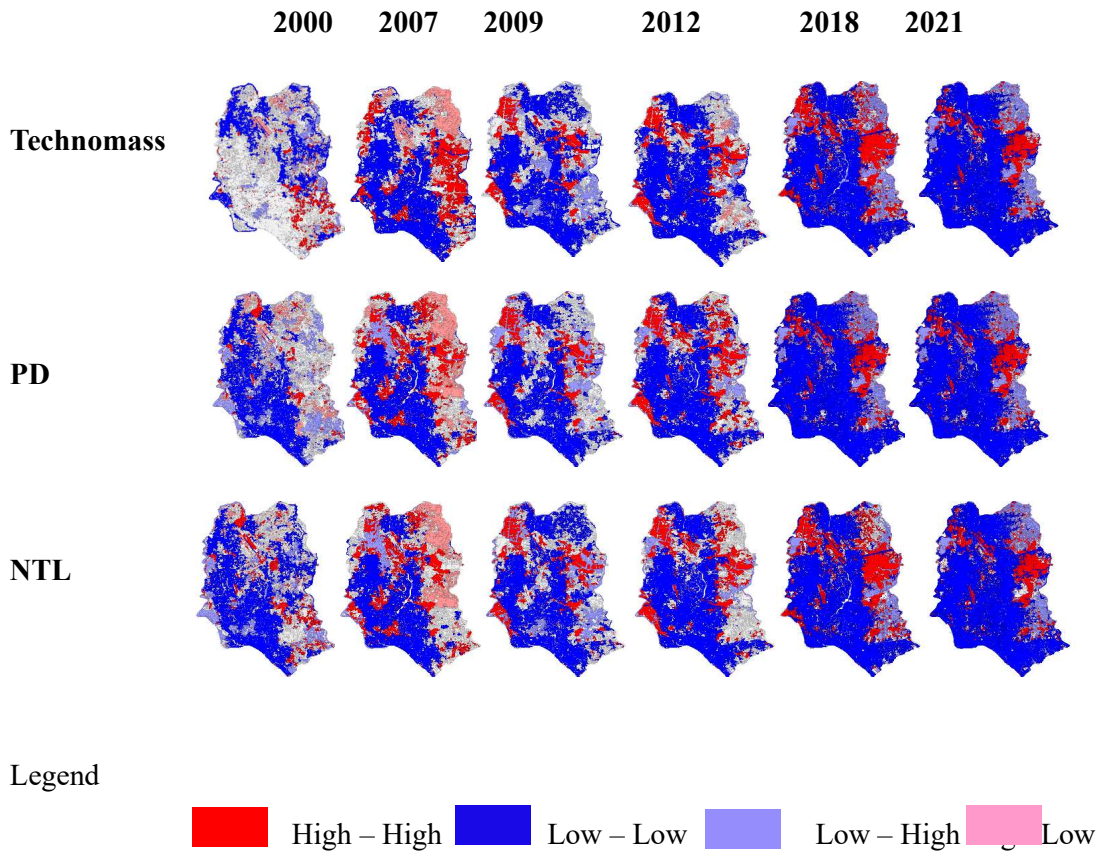


Figure 5. 8 Bivariate LISA cluster maps between different types of urbanization indicators and ESV

5.4 Conclusion

During the study period, the overall degree of urbanization in Dhaka city increased. This increase led to a decrease in ecosystem service values (ESV) across vegetation cover, agricultural land, and water body areas. The temporal relationship between urbanization and ESV, analyzed using a Geographically Weighted Regression (GWR) model, revealed a nonstationary relationship. The GWR model examined the geographic spatial relationships between urbanization indicators and ESV changes, showing that technomass had a strong negative association with ESV. Bivariate Local Indicators of Spatial Association (LISA) cluster maps indicated that areas with high urbanization levels corresponded with very low ESV values.

Recognizing this dynamic temporal interrelationship is crucial for adjusting ecological policies and urban development patterns across different zones of Dhaka city to achieve sustainable development. Additionally, the values of different ecosystem services (ES) did not change sustainably during urbanization. Provisioning, regulating and maintenance, and cultural services continued to decline due to the reduction in agricultural land, vegetation cover, and water bodies.

Optimizing land-use structures to conserve and enhance specific ES, while reducing negative tradeoffs and promoting positive synergy with other ES, is necessary. This study highlights the promise of employing technomass analysis techniques to understand the spatiotemporal dynamic evolution of the relationship between urbanization and ESV. The government should emphasize various aspects of urbanization and selectively promote ecological protection, restoration, and construction within the identified spatial clustering areas

Chapter 6

Evaluating the Cooling Potential of Ecosystem Services in Dhaka City, Bangladesh, to Mitigate Urban Heat Islands Resulting from Urbanization through Nature-Based Solutions

6.1 Introduction

The urban ecosystem, especially the urban thermal environment, has been adversely impacted by rising urbanization and population growth. This urbanization has shown a rapid upward trend during the last sixty years. The global urban population has grown from 751 million in 1950 to 4.2 billion in 2018 (Marando et al., 2019) and it is estimated that the global urban population will reach 6.68 billion by 2050, which directly accounts for 68% of the world population (M. Chen et al., 2022). The urban area is expected to reach up to 0.9-1 million km² in 2050, which is about twice the urban area in 2000 (G. Chen et al., 2020). This excessive urbanization may lead to a higher building area ratio in the city, which makes the heat collected in the city difficult to diffuse and accelerates the intensity of the urban heat island (M. Zhang et al., 2023). Urban heat island (UHI) was first described in the year 1818 as a phenomenon in which urban areas have higher atmospheric and surface temperatures than the surrounding rural areas (Howard, 1833). Landscape changes due to urban development, reduced vegetation cover in urban areas, properties of urban materials, urban geometry, anthropogenic heat, weather, and geographic location are among the various general factors influencing the formation of UHI (X. Zhang et al., 2017). High temperatures in cities are a major environmental concern as it is associated with a range of negative impacts such as heat-related health problems (Z. Yin et al., 2023), mortality (Yadav et al., 2023), and threats to biodiversity (Qiu et al., 2023).

Biophysical assessments of vegetation cover's heat mitigation capacity can be conducted using air temperature measurements and analysis of remotely sensed land surface temperature (LST) imagery (Zawadzka et al., 2021). The recently developed Urban Cooling model, part of the InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) suite from the Natural Capital Project, simplifies the assessment of vegetation cover's urban heat island (UHI) mitigation capacity (Natural Capital Project, 2024). InVEST

includes spatially explicit ecosystem service models for terrestrial, freshwater, marine, and coastal ecosystems, aiming to assess synergies and trade-offs in natural resource management.

The Urban Cooling model calculates the heat mitigation index (HMI) based on vegetation cover evapotranspiration, the cooling distance of large urban parks, and land cover (LC) albedo, estimating average Cooling effects and the monetary value of vegetative cooling (Zawadzka et al., 2021). The European Commission has prioritized sustainable urbanization through Nature-Based Solutions, which involve the sustainable management and use of natural processes to address socio-environmental issues (Bauduceau et al., 2015). These solutions integrate nature and natural processes into urban areas to tackle environmental and socio-ecological challenges through locally adapted, resource-efficient, and systemic interventions (Faivre et al., 2017).

One effective Nature-Based Solution for sustainable urban growth is the enhancement of urban Green Infrastructure (GI) (Vegetation cover, agricultural land, waterbody), a network of natural, semi-natural, and artificial vegetation cover that provide a wide range of Ecosystem Services (ES) (European Commission, 2024). GI significantly mitigates UHI and associated health risks, known as the ES of climate regulation (CICES Code 2.2.6.2, 2.2.6.1, 2.2.5.1, 2.1.1.1) (Haines-Young & Potschin-Young, 2018). Urban vegetation cover can lower air temperatures by 1-3 °C, and up to 5-7 °C cooler than nearby built-up areas, with effects extending to the surroundings (Y. Zhang et al., 2017). Thus, enhancing GI is an effective tool for mitigating UHI, especially during hot summers in tropical climates.

Dhaka, one of the world's most densely populated cities (H. Yin et al., 2021), is experiencing intensified urban heat islands (UHIs), which decrease overall livability (Faisal et al., 2021). The daytime and nighttime surface UHI intensities in Dhaka have significantly increased over the years at rates of 0.03 °C per year and 0.023 °C per year, respectively (Uddin et al., 2021). This degradation negatively impacts the cooling capabilities of ecosystem services (Livesley et al., 2016). (A. Dewan, Kiselev, Botje, et al., 2021) examined surface UHI intensities in five major cities of Bangladesh, identifying population density, lack of greenery, and anthropogenic factors as major contributors to UHI intensities. A study on the canopy-layer UHI in Dhaka from 1987 to 2016, using air temperature data

from Dhaka and the nearby suburban area of Savar, found a maximum UHI intensity of 3.5 °C (Khatun et al., 2020). While these studies provide a comprehensive understanding of UHI characteristics in Dhaka, further investigation is needed in several areas.

Quantifying the Cooling effects of green infrastructures to mitigate UHIs in Dhaka requires more research, which is crucial for urban planning and decision-making (Korkou et al., 2023; Mosissa et al., 2023). Studying the temporal heat mitigation capacity of green structures is essential for long-term sustainable city planning.

This study aims to fill this gap by proposing an approach to estimate the Cooling effects of green infrastructure (GI) to support urban planning. It emphasizes the need for urban planners to integrate ecosystems into their planning practices to cool cities and combat UHIs. The study objectives are to:

1. Characterize the spatiotemporal Surface Urban Heat Island (SUHI) phenomenon in Dhaka,
2. Assess the heat mitigation patterns in Dhaka using the InVEST Urban Cooling Model, and
3. Quantify the temporal heat mitigation provided by vegetation cover on ecosystem services.

6.2 Materials and Methods

6.2.1 Study Area

Dhaka, the capital city of Bangladesh, is located between 23.71° N latitudes and 90.41° E longitudes (Fig. 6.1) and has a total area of 306.4 km². It is one of the most populated cities in Bangladesh and the world, with almost 22.47 million people (Dhaka, Bangladesh Metro Area Population 1950-2022). The city includes two city corporations, namely Dhaka South City Corporation (DSCC with 57 wards) and Dhaka North City Corporation (DNCC with 36 wards) along with the fringe area with 17 unions. The study area is divided into five regions namely the old central business district (OCBD) area having Motijheel, Ramna, Dhanmondi, Agargaon; the newly developed CBD (NCBD) area having Gulshan, Banasree, Badda, Baridhara, Nikunja, new industrial (NI) area having Tejgaon, Begunbari; old housing and old industrial (Inner City) area having Bangshal, Jatrabari, Hazaribagh, Mohammadpur; rural-urban fringe (Fringe Area) having Khilgaon, Beraid, Dumni, Kanchkura, Uttar Khan, Mainertek, Bamnartek, Agunda, and Gabtoli (Capital city authority, Dhaka, Bangladesh, 2018; Rahman et al., 2021). The city is surrounded by three major rivers: Turag to the northwest, Buriganga-Dhaleshwari to the south, and Shitalakhy-Balu to the east. More than 80% area has been urbanized and the population density is 30,474 and 39,353 inhabitants per square kilometer in the north and south city corporations (BBS, 2022).

Due to rapid urbanization, Dhaka, the capital of Bangladesh, is increasingly unable to sustain outdoor life because of urban heat island (UHI) effects, a well-documented phenomenon of urban climate change. UHI intensity in and around Dhaka ranges from 2.5°C to 7.5°C, leading to increased demand on urban energy resources for cooling (Al Shanto et al., 2024). Nature-based mitigation of surface urban heat islands (SUHI) is essential for achieving Sustainable Development Goal 11.

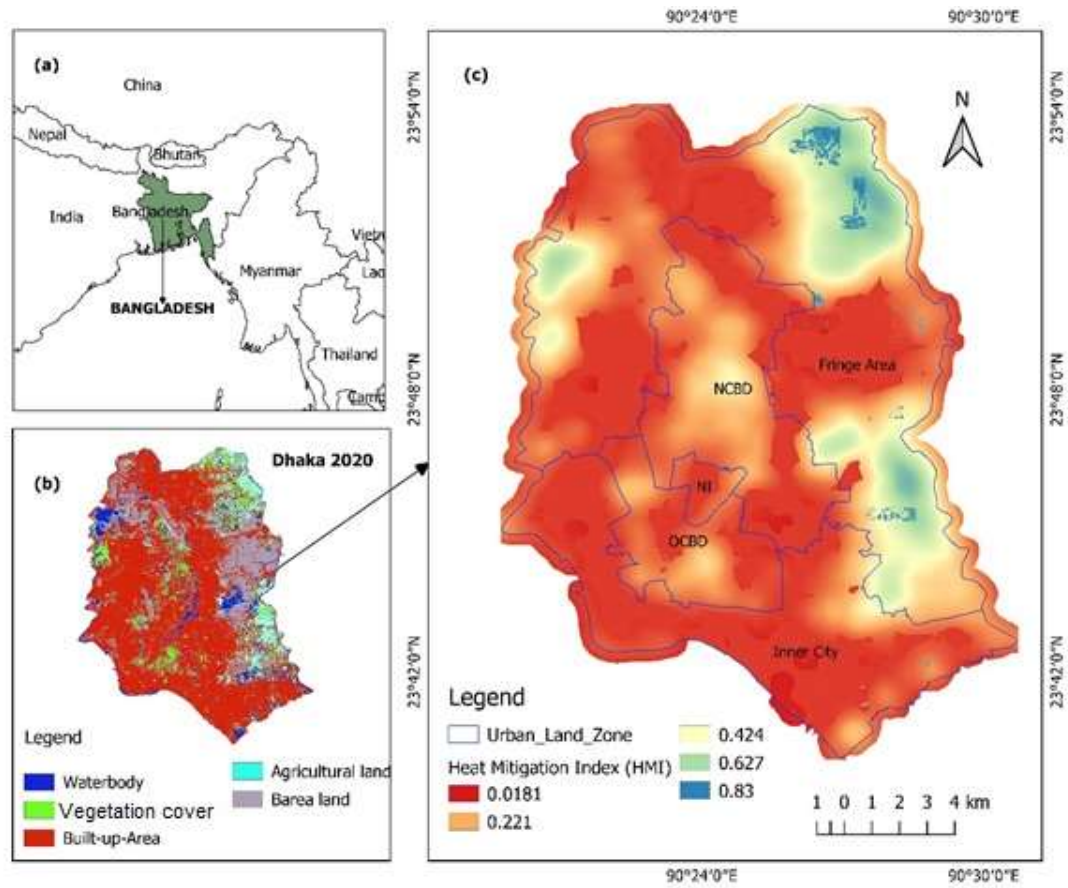


Figure 6. 1 Study area (a) location of Bangladesh, (b) LULC of Dhaka (2020), and (c) HMI of Dhaka (2020).

6.2.2 Datasets

Remote sensing data with different spectral and spatial resolutions, along with DEM datasets, were utilized to analyze the horizontal and vertical growth of the city (Table 1).

Table 6.1 Datasets used in this study.

Data	Resolution	Sources	Acquisition Date
Landsat 5	30m	https://earthexplorer.usgs.gov/	2000,2007,2009,2012
Landsat 8	30m	https://earthexplorer.usgs.gov/	2018,2020
Global Surface Urban Heat Island (SUHI)	300 m	https://yceo.users.earthengine.app/view/uhimap	2000-2020

6.3 Identification of Ecosystem Functions and Components

One of the most powerful strategies for promoting sustainable urban development is the utilization of urban Green Infrastructures (GI), which encompasses natural, semi-natural, and artificial vegetation cover and offers a diverse range of ecosystem services (ES) (Bauduceau et al., 2015; Marando et al., 2019; Tzoulas et al., 2007). In Dhaka city, the primary elements of GI are represented by vegetation cover, including parks situated within the city core and its immediate surroundings, street trees (stand-alone trees on roadsides surrounded by paved ground), and other vegetation cover like lawns and water bodies (Nahin et al., 2023).

6.4 Land Surface Temperature (LST) and LULC classification

Atmospherically corrected surface reflectance Landsat 8 OLI/TIRS data were used to derive the land surface temperature. This image contains 5 visible and near-infrared (VNIR) bands 2 short-wave infrared (SWIR) bands processed to orthorectified surface reflectance and one thermal infrared (TIR) band processed to orthorectified surface temperature (USGS Landsat 8 Level 2, Collection 2, Tier 1 | Earth Engine Data Catalog | Google for Developers, 2023). This study used the methodology developed by (Weng et al., 2004) for spectral radiance to at satellite brightness temperature (T_B , °C) by

the following eq. (1).

$$T_B = K_2 / \ln [(K_1 / L_\lambda) + 1] - 273.15 \quad (11)$$

Where K_1 and K_2 are band-specific thermal conversion constants measured in $\text{w/m}^2 \cdot \text{sr} \cdot \mu\text{m}$ and K , respectively, L_λ is the Spectral Radiance at the sensor's aperture, measured in $\text{w}/(\text{m}^2 \cdot \text{sr} \cdot \mu\text{m})$, and 273.15 is the conversion factor from K to °C. T_B was then used for Land Surface temperature (LST, °C) retrieval according to Eq. (2) (Marando et al., 2019; Weng et al., 2004).

$$LST = \frac{T_B}{\left[1 + \frac{\lambda T_B}{P}\right] \ln \varepsilon} \quad (12)$$

The sign λ denotes the wavelength of the emitted thermal radiance, p denotes the wavelength of the emitted thermal radiance $1.438 \times 10^{-2}\text{mk}$ and ε is the land surface emissivity (Tariq & Mumtaz, 2022). This study derived four radiometric indices from sentinel image: the Normalized Difference Vegetation cover Index (NDVI) for assessing vegetation cover (Ezaidi et al., 2022), the Modified Normalized Difference Water Index (MNDWI) for detecting water bodies (Haldar & Majumder, 2022), the Normalized Difference Built-Up Index (NDBI) for identifying built-up areas (Zha et al., 2003) and the Bare Soil Index (BSI) for distinguishing bare soils (Wanhui Chen et al., 2004). These indices were integrated into an image classification process on the Google Earth Engine platform to ensure accurate land use classification. The classification was carried out using a random forest (RF) classifier (Breiman, 2001). To validate the generated land cover data, this study compared them with Google Earth images and previously available national statistics datasets (BBS (Bangladesh Bureau of Statistics), 2022; Capital city authority, Dhaka, Bangladesh, 2018). This process resulted in the identification of five land cover classes: Water bodies, vegetation cover, built-up areas, agricultural land, and bare soils. The accuracy of LULC classification for the study was calculated as 89.22% for producer accuracy and 87.23% for user accuracy. The classification and accuracy assessment were carried out for the year 2021 for this study.

6.5 Spatial Analysis of Surface Urban Heat Island (SUHI)

The Surface Urban Heat Island (SUHI) is the temperature difference between the city core and the periphery. This SUHI dataset includes annual, summer, and winter surface urban heat island intensity data for both daytime and nighttime observations across more than 10,000 urban clusters worldwide. This dataset was generated by utilizing the MODIS 8-day TERRA and AQUA Land Surface Temperature (LST) products, the Land scan urban extent database, the Global Multi-resolution Terrain Elevation Data, and the European Space Agency (ESA) Climate Change Initiative (CCI) land cover data through the Simplified Urban-Extent Algorithm. (Global Surface UHI Explorer | Center for Earth Observation, 2023). This dataset can be utilized within the Google Earth Engine platform to compute SUHI intensity for more than 9500 urban clusters, leveraging a dataset spanning over 15 years. This marks it as one of the most extensive SUHI databases (Feng et al., 2021). This study calculated SUHI from this database and validated this data using LST. This study assessed the SUHI data by comparing it to the Heat Mitigation Index (HMI) produced by the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) urban cooling model (UCM).

6.6 InVEST Urban Cooling Model

The InVEST 3.12.1 UCM generates heat mitigation index (HMI) maps, which estimate the cooling capabilities of urban vegetation cover for all land cover classes in the study area. This estimation includes the cooling potential of larger urban parks that extend beyond their designated boundaries (InVEST® User Guide, 2023) . The heat mitigation is computed based on biophysical properties defined for each land use category, shade factor (ranging from 0 to 1, 0 for no tree and 1 for full tree cover), an evapotranspiration factor (ET factor), and an albedo (0–1) (Kadaverugu et al., 2021; Zardo et al., 2017; Zawadzka et al., 2021).

6.6.1 Model Parameterization and Data Sources

The key inputs consist of a raster map illustrating land use/land cover, a reference evapotranspiration raster, and a biophysical table containing model information for each land use/land cover class depicted on the map. In this research, cloud-free Sentinel-2A

images (Earth Explorer <https://earthexplorer.usgs.gov> portal) are utilized to generate land use/land cover (LULC) data over the study area for 2021 at a spatial resolution of 10 meters (Fig. 1). The map was classified by applying 4 radiometric indexes NDVI, MNDWI, NDBI, BSI. The parameters assigned to each LULC class are evapotranspiration coefficient, albedo, cooling distance away from large greenspaces, as well as greenspace and shading (Table 1). Shading and evapotranspiration (ETA) are key regulating ecosystem functions of that vegetation cover that contribute to Cooling effects (Stumpe et al., 2023; Tams et al., 2023). Additionally, vegetation cover influences the urban microclimate through three main mechanisms: (i) by intercepting incoming solar radiation (providing shade); (ii) via the process of evapotranspiration; and (iii) by modifying air circulation and heat exchange patterns (Jordan et al., 2023; Zardo et al., 2017). In this research, the study used shade and evapotranspiration regulating ecosystem functions data as InVEST urban cooling model input for estimating the Cooling effects of GI. Evapotranspiration coefficients for the primary land use/land cover (LULC) classes in the study area were estimated based on existing guidelines for calculating crop evapotranspiration, (Allen et al., 1998) as recommended in the InVEST User Guide.

Table 6.2 Key parameters assigned to each land cover class within the study area are submitted to the model as the biophysical table.

LULC	Shade	Kc	Albedo	Greenspace
Waterbody	0	0.65	0.09	1
Vegetation cover	1	0.95	0.18	1
Built up area	0	0.0001	0.25	0
Agricultural land	0	0.95	0.16	1
Bare land	0	0.0001	0.14	0

Albedo values for individual land use/land cover (LULC) classes were derived by considering the highest absorption of solar radiation by water, followed by paved areas due

to the dark color of asphalt roads. In contrast, buildings were assigned the lowest albedo values, while vegetated areas received intermediate values (Taha et al., 1988; Zawadzka et al., 2021). This study considered the water and vegetation cover as a green space following the methodology for Cooling effects estimation presented by (Zardo et al., 2017) (Fig. 2). Distances for cooling effects away from large vegetation cover were considered, specifically at 450 meters. This distance approximation aligns with the reported ranges in the literature concerning the Cooling effects of urban parks, spanning from 20 to 450 meters (Aram et al., 2019; Vaz Monteiro, Doick, Handley, & Peace, 2016). The model necessitated additional settings, namely the air temperature reference value (<http://www.barc.gov.bd/>) and the UHI magnitude (<https://yceo.users.earthengine.app/view/uhiimap>) These settings were essential for the model to execute and generate the heat mitigation index (HMI).

6.7 Assessment of the Cooling effects of Different Ecosystems

The study assessed the mitigating impact of various ecosystems on heat mitigation through buffer analysis. Two distinct ecosystems, namely vegetation cover and water bodies, were chosen for evaluation. Buffers, each with a width of 100 meters, were employed to examine Heat Mitigation Index (HMI) variations from the periphery of each ecosystem extending up to a maximum distance of 400 meters towards the built-up area. Subsequently, the average HMI difference between each buffer and the core of the respective ecosystem was computed to ascertain the Cooling effects of each ecosystem. This analysis encompassed both the reduction in Land Surface Temperature (LST) in degrees Celsius and the maximum distance for effective cooling from the ecosystem boundaries.

6.8 Spatial Correlation between Cooling effects of Vegetation cover and Heat Mitigation Index (HMI)

In this study, two spatial analysis techniques were applied. First, the geographically weighted regression (GWR) model to examine the spatial non-stationary relationship between vegetation cover and heat mitigation index at the local level. A comprehensive investigation of this spatial heterogeneity is beneficial for decision-makers in formulating tailored policies (W. Chen et al., 2019; Xing et al., 2021). Second, this research employed GeoDa 1.22.0.2 software to unveil the distinctive spatial characteristics of HMI in conjunction with vegetation cover. Local spatial autocorrelation, as depicted by LISA (Local Indicators of Spatial Association) cluster maps, describes the spatial interrelations among attributes across different spatial units (Anselin, 1995; C. Peng et al., 2021; Zhu and Cai, 2023): which can be summarized as (i) High-High aggregation, indicating regions with high attribute values are surrounded by other regions with high attribute values ; (ii) Low-Low aggregation, indicating a regions with low attribute values are surrounded by other regions with low attribute values; (iii) Low-High aggregation, indicating a regions with low attribute values are surrounded by other regions that have high attribute values; and (iv) High-Low aggregation, indicating a regions with high attribute values are surrounded by other regions with low attribute values. Furthermore, this study employed Pearson's correlation analysis to explore the connections between LST and HMI. When assessing correlations among continuous data factors, Pearson's correlation analysis is often favored for delivering more robust and consistent results compared to alternative correlation analysis methods. Consequently, it is frequently used to infer the interactions between LST and HMI (Kim et al., 2020; Niu et al., 2022; Shi et al., 2021; M. Yang et al., 2023).

6.9. Results and Discussion

6.9.1 Characteristics of LULC and LST in Dhaka City

6.9.1.1 Spatial Characteristics of LULC

The Land Use and Land Cover (LULC) analysis of Dhaka has revealed a consistent increase in the built-up area from 2000 to 2020, a trend commonly observed in metropolitan cities of developing countries. The concentration of built-up areas was highest in the city's core, gradually expanding to the outskirts. The findings indicate that the built-up area is the predominant class, having increased by 94.94%, while water bodies decreased by 70.93%. Bare land increased until 2018; after that, it decreased due to its conversion into built-up areas. On the other hand, agricultural land decreased by 60.08%, particularly in rural-urban fringe areas. High-density residential zones are primarily located in the central parts of Dhaka, while low-density residential areas are situated along the fringe. Among the various land cover types, agricultural land and vegetation cover have the lowest percentages at 6.97% and 6.65%, respectively, in 2021, compared to 18.97% and 20.36% in 2000. Bare land emerges as the second dominant land cover type, constituting more than 18% of the total area across all five land cover types in 2020 (Fig. 6.2).

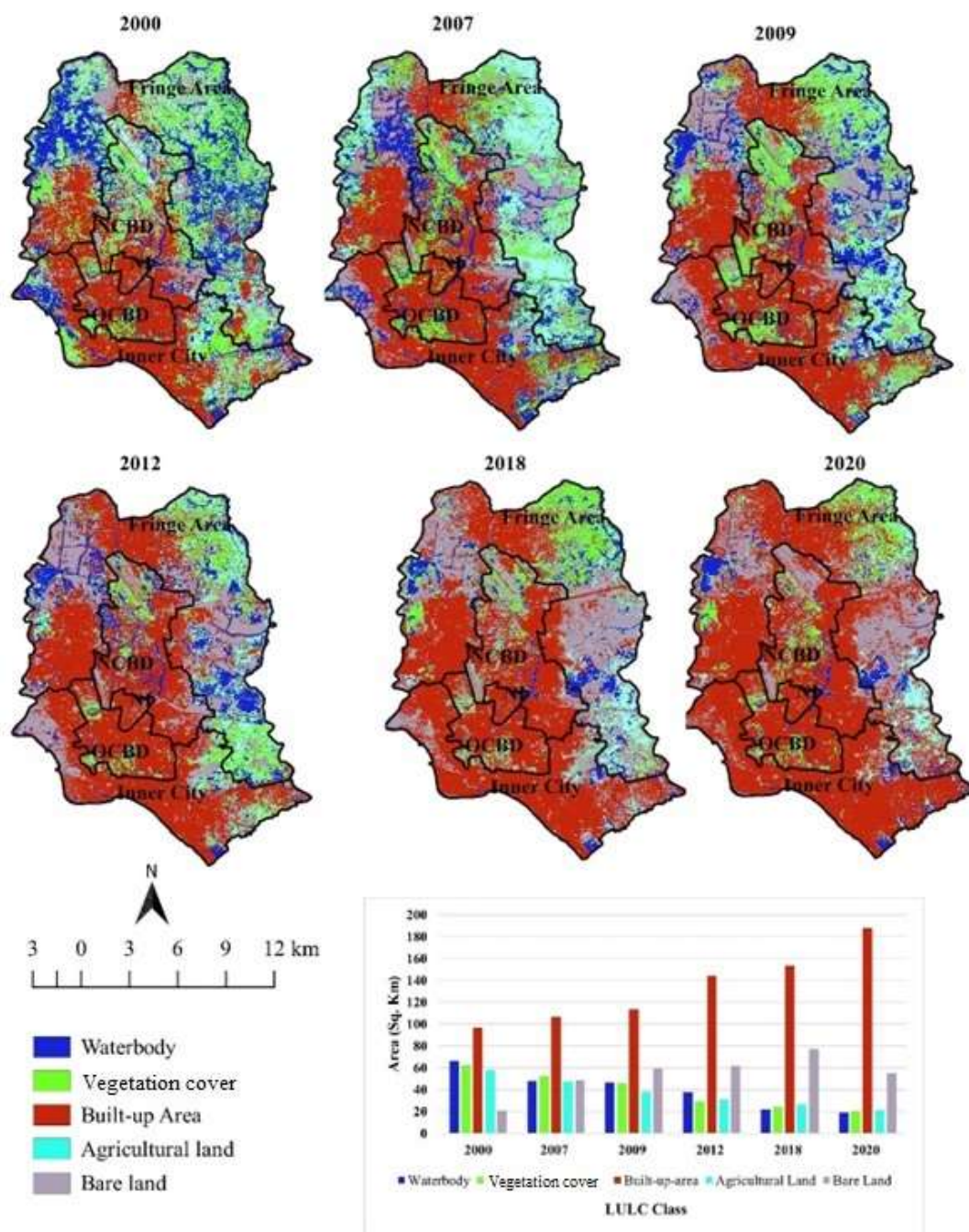


Figure 6. 2 LULC maps of the study area (2000-2020)

6.9.1.2 Spatial Pattern of Land Surface Temperature (LST)

The spatiotemporal distribution of Land Surface Temperature (LST) was calculated using the Landsat thermal bands across the study area. The annual distribution of LST from 2000 to 2020 is illustrated in (Table 6.3.), depicting the spatial pattern of LST. Zonal statistics were applied to compute the mean LST for different zones. The results indicated that in 2000, the mean temperature recorded was 31.98°C, experiencing a significant increase to 36.59°C in 2020, with a yearly change of 0.23°C (Table 6.3). The mean summer temperature data for the years 2000, 2007, 2009, 2012, 2018, and 2020 were obtained from the Bangladesh Agricultural Research Council (BARC) (<http://www.barc.gov.bd/>) to validate the estimated LST values derived from remote sensing data. On average, a deviation of $\pm 0.13^{\circ}\text{C}$ was observed throughout the study period. Despite the inherent limitations of remote sensing-based estimated LST values, the minor differences between estimated and measured LST can be acknowledged and utilized for further analysis in this study.

Table 6.3 Thermal bands estimated mean zonal LST

	Land Surface Temperature (LST) °C					
	2000	2007	2009	2012	2018	2020
OCBD	31.87	37.22	30.97	33.84	36.56	35.76
NCBD	32.80	36.72	29.93	33.78	36.07	37.08
NI	33.11	40.31	32.28	35.72	38.56	37.27
Inner City	31.03	36.80	30.94	34.35	37.19	36.41
Fringe Area	31.07	34.02	29.32	32.49	34.90	36.44

6.9.2 Spatial Characteristics of SUHI Changes over Different Land Classes

The SUHI values in Dhaka demonstrate noticeable changes corresponding to the Land Use and Land Cover (LULC) classification (Fig.6.4). The areas with the lowest SUHI values are predominantly situated around the urban fringe, where water, and vegetation cover are prevalent, as well as along the city's larger urban vegetation cover (Fig.6.3). Intermediate SUHI values are observed in the NI and NCBD areas, characterized by the presence of grasslands and water bodies. In the urbanized core of the city, there is the lowest proportion of vegetation cover and the highest average SUHI. In the suburban regions, the average SUHI decreases while the proportion of vegetation cover increases. The OCBD region exhibits the highest SUHI effect, reaching an intensity of 8.37 °C in 2012. In contrast, the lowest SUHI of 1.18 °C was recorded in 2020 when commercial activities were minimal in NI region. This dataset was utilized as input for the InVEST urban cooling model.

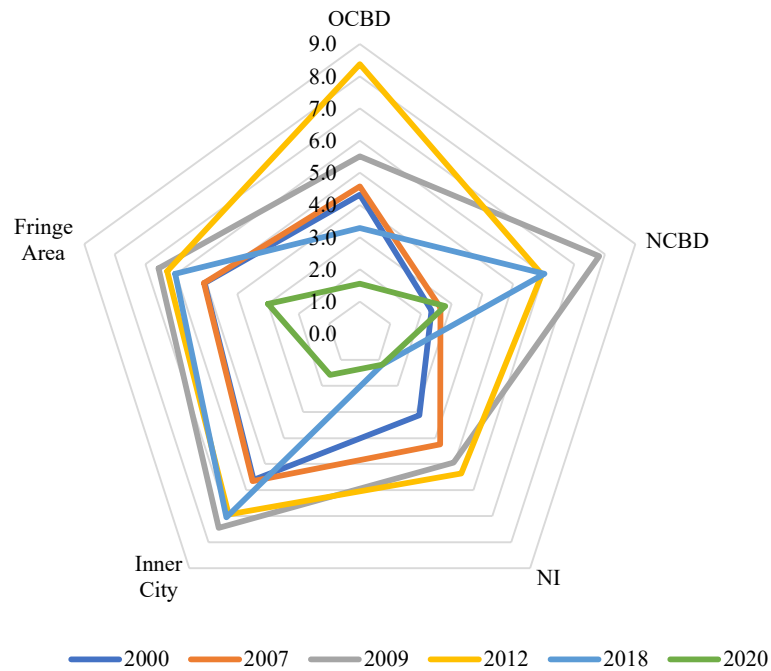


Figure 6. 3 Spatial pattern of Surface Urban Heat Island (SUHI) °C

The estimated mean Surface Urban Heat Island (SUHI) distribution across different Land Use and Land Cover (LULC) classes from 2000 to 2020 was calculated using the zonal statistics tool in QGIS 3.2.1 software (Fig. 3). Throughout the study period, the mean

SUHI experienced an increase in each LULC class, with particularly noticeable rises in the built-up area and bare soil. Specifically, the mean SUHI values for the built-up and bare soil areas increased from 2.75°C to 3.24 °C and 1.12 °C to 1.47 °C, respectively, between 2000 and 2018. However, in 2020, all SUHI values decreased due to reduced commercial activities during the COVID-19 breakout. The most significant reduction occurred in this time in the built-up area, dropping from 2.75°C to 1.01°C, and in the bare soil, decreasing from 1.12°C to 0.52 °C. Over the past 18 years, the mean SUHI distribution has shown an overall increase of 0.50 °C and 0.35 °C in both built-up and bare soil areas. Changes in SUHI distribution were also observed in water bodies and vegetated areas. In 2000, the estimated mean SUHI value for vegetation cover was 0.68 °C, which increased to 0.91 °C in 2018. Similarly, in water bodies, the mean SUHI value increased from 0.60 °C to 0.78 °C. The highest recorded mean SUHI value was 3.24 °C in the built-up area in 2018, while the lowest value was 0.32 °C in the vegetation cover class in 2020 (Fig. 6.4).

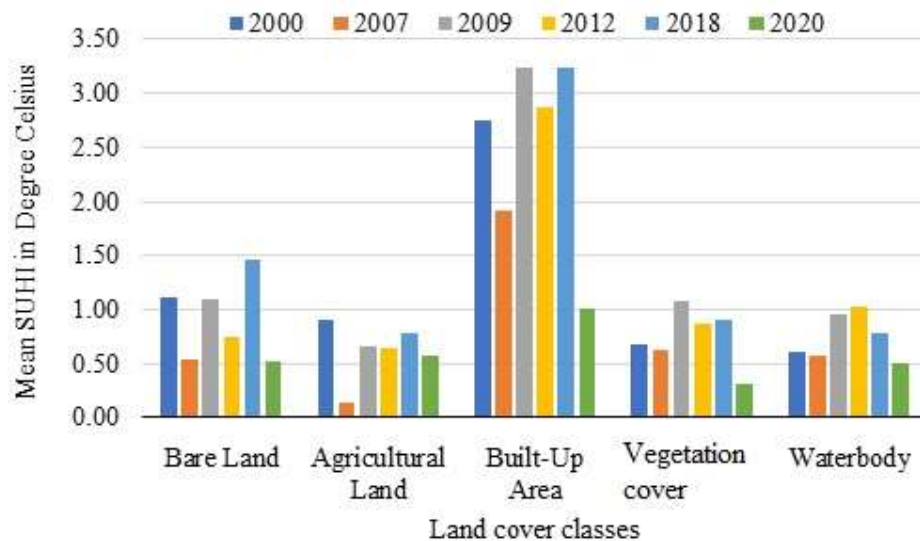


Figure 6. 4 Mean SUHI over different LULC classes from 2000 to 2020.

6.9.3 Spatiotemporal Heat Mitigation Pattern in Dhaka City

Like many other megacities in Asia, Dhaka is also experiencing severe environmental degradation, leading to a continuous decline in natural ecosystems and their associated services. One of the most critical functions of ecosystem services is their ability to regulate air temperature and water quality (L. Zhao et al., 2023). The loss of vegetation cover creates urban heat islands that severely affect public health (Tawfeeq Najah et al., 2023). Vegetation cover in Dhaka city serve as natural filters, removing pollutants and reducing the risk of various health impacts. However, due to urban expansion, these vegetation covers are significantly decreasing. The changes in the urban built-up area over multiple time scales indicate that the new construction has taken place both within the city limits and at the fringes (Fig.6.5).

This study utilized the InVEST UCM model for calculating the temporal changes of heat mitigation scenarios for Dhaka city. The index ranged from zero to one, with values in red representing low heat mitigation and values in blue representing high heat mitigation. The HMI corresponded to an area's ability to cool down due to trees, water, or other factors. The study used zonal statistics using GIS to calculate the region-wise mean value of HMI. Results showed that the rural-urban fringe area had the highest mean value of HMI in 2000 (69.85%), while the new industrial area had the lowest (20.36%). HMI significantly decreased over the study period in the new industrial area (-64.58%), followed by OCBD (-62.42%), Fringe area (-44.37%), NCBD (-33.22%), and Inner city (-28.44%). The conversion of vegetation cover to other land use types led to a heat mitigation capacity loss mostly in fringe areas and newly developed central business districts (CBD).

Regions with higher HMI were mostly found in areas with better hydrological conditions and vegetation cover, such as the northeastern, southeastern, northwestern, and southwestern regions. Agricultural land and waterbodies were converted to bare land for urban expansion, leading to the continuous destruction of Cooling effects in the fringe area of the city. The first noticeable pattern in this map is that the surrounding rural areas are generally cooler than the city. OCBD and NI were the hottest areas on the map, which suggests a need for green infrastructure measures here. This hot area corresponded spatially to having a high surface urban heat island (SUHI) at 4.60 °C and 3.34 °C, respectively.

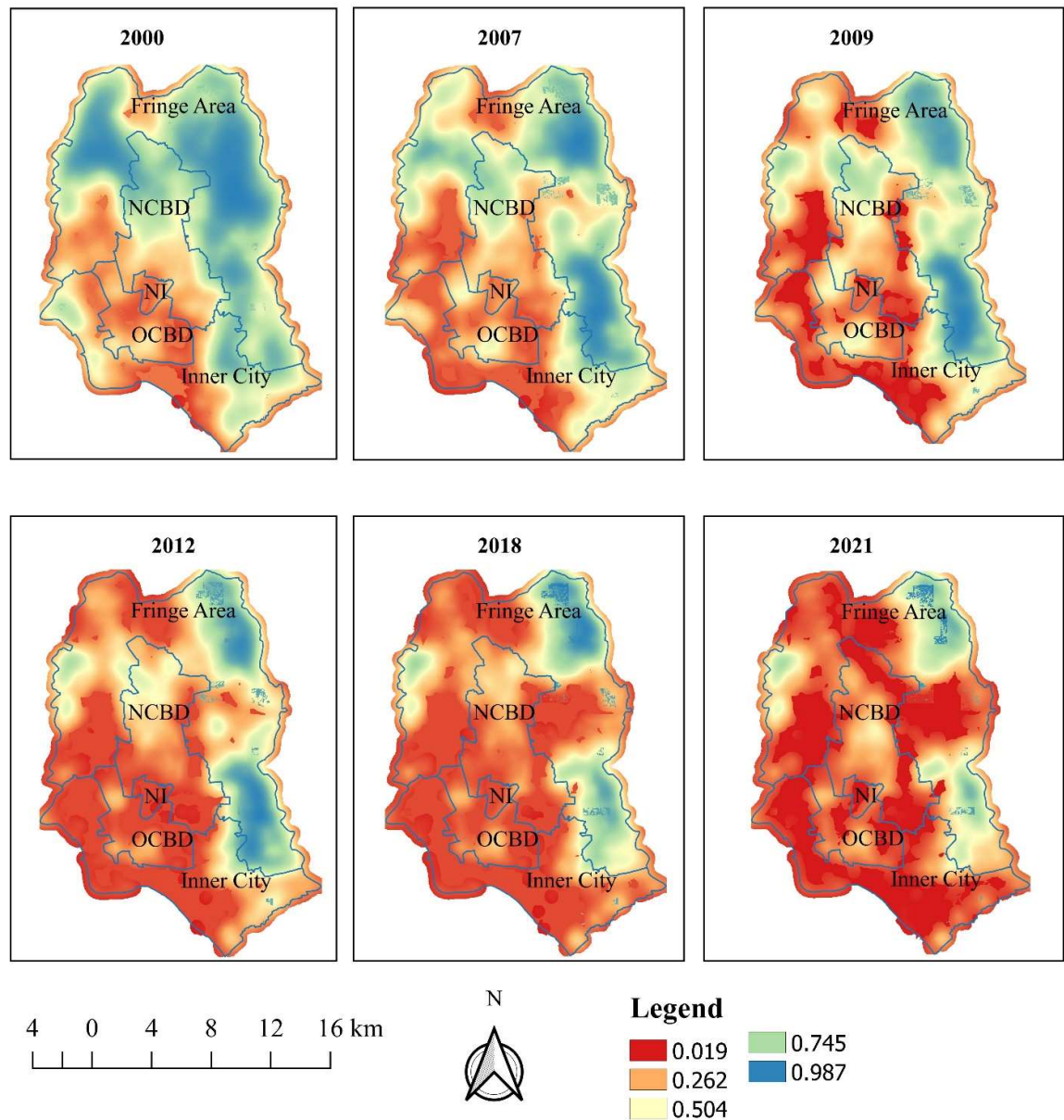


Figure 6. 5 Spatially distributed heat mitigation index (HMI) in Dhaka from 2000-2020

6.9.4 Spatiotemporal Assessment of HMI within Individual LULC Types

Based on the results of the InVEST urban cooling model, it was found that the average Cooling effects index values decreased from 0.57 to 0.30 between 2000 and 2020, indicating a (47.55%) reduction rate. In 2000, the mean Heat Mitigation Index (HMI) comprised vegetation cover (23.77%), water bodies (22.72%), and agricultural land (22.37%) in total Cooling effects (CC), while built-up land accounted for just (12.23%). From 2000 to 2009, the mean HMI of Dhaka decreased from 0.57 to 0.46 (18.88%). The HMI of vegetation cover, water bodies, agricultural land, built-up area, and bare soil all declined significantly in terms of land use/cover types by 19.11%, 20%, 6.24%, 31.42%, and 24.07%, respectively.

During the period 2009 to 2020, the HMI of Dhaka decreased from 0.46 to 0.30 (35.34%). The HMI for water bodies, vegetation cover, built-up area, agricultural land, and bare soil also decreased by 40.38%, 25.45%, 33.33%, 33.34%, and 46.34%, respectively. The concentration of high heat mitigation indexes is observed in water bodies and vegetation cover land class. The cooling effect is directly proportional to the size of this vegetation cover, and the cooling distance is strongly correlated with the tree canopy (Z. Yu et al., 2020). This result shows that the vegetation cover in the area can provide natural cooling effects through natural shading. (Steeneveld et al., 2011) noted a decrease of 0.6 °C in the Urban Heat Island (UHI) index with a 10% increase in vegetation cover. In a related study, (Ng et al., 2012) estimated that tree cover should be 33% of the urban area to drop the air temperature by 1 °C. However, in Dhaka city, there has been a notable 34% decrease in vegetation cover and a substantial 94.94% increase in built-up areas throughout the study period. As a result, the surface urban heat island (SUHI) index increased by 1.18°C

Table 6.4 Mean distribution of HMI over different LULC classes from 2000 to 2020

	2000	2007	2009	2012	2018	2020
Waterbody	0.65	0.54	0.52	0.43	0.40	0.31
Vegetation cover	0.68	0.56	0.55	0.52	0.46	0.41
Built-Up Area	0.35	0.29	0.24	0.21	0.16	0.16
Agricultural Land	0.64	0.70	0.60	0.57	0.39	0.40
Bare Land	0.54	0.44	0.41	0.29	0.25	0.22

6.9.5 Correlation of HMI Changes due to the LST

Regression analysis was employed to examine the heat mitigation pattern in Dhaka as simulated by the InVEST UCM, and it was compared with daytime Land Surface Temperature (LST) data for the summers spanning from 2000 to 2020. The Heat Mitigation Index (HMI) was determined based on the Cooling effects of vegetation cover, while the LST data were obtained from the thermal infrared band of Landsat 8. The analysis revealed a strong correlation between HMI and LST, with an observed R^2 value of 0.77.

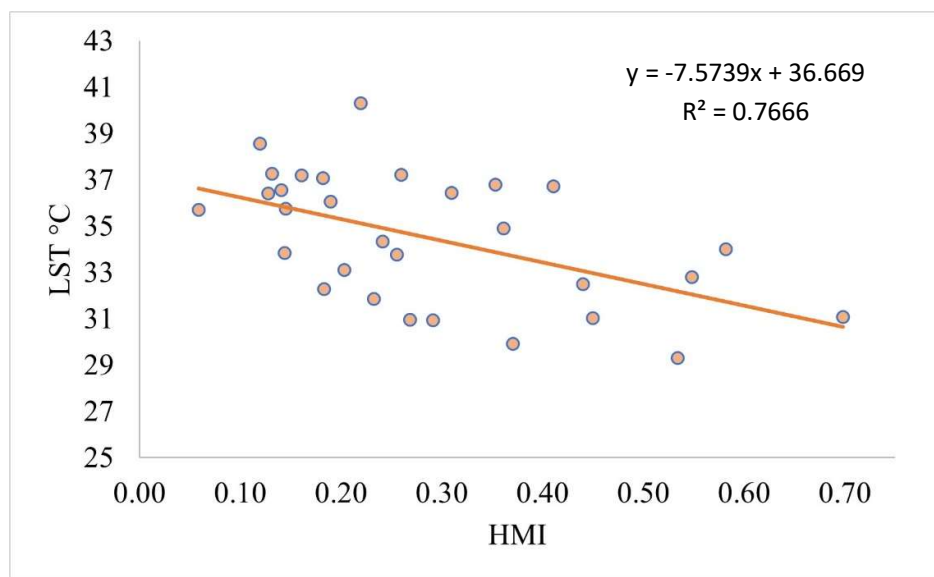


Figure 6. 6 Correlation between HMI and LST in Dhaka from 2000-2020

A negative correlation was observed between LST and HMI, suggesting that an increase in LST corresponds to a decrease in HMI. To assess these changes, a Pearson's correlation analysis test was conducted using RStudio. The results revealed a significant negative correlation ($p < 0.01$) between LST and HMI ($r = -0.77$). In the zonal statistics analysis, the rural-urban fringe area exhibited the most substantial negative correlation ($r > -0.70$) in HMI changes, followed by the inner city ($r > -0.61$), NCBBD ($r > -0.46$), OCBBD ($r > -0.40$), and NI region ($r > -0.06$).

6.10 Conclusions

According to the International Energy Agency (IEA, 2024), buildings contribute to 30–40% of global energy consumption. In regions with tropical climates, the implementation of green roofs has been identified as an effective measure to alleviate Urban Heat Island (UHI) effects (J. Yang et al., 2018) and in every 1000 m² increase in the green roof area, the average LST of the roof decreased by 0.4 °C (Zheng et al., 2022). This research revealed that the built-up area expanded in Dhaka by 94.94%, Heat mitigation capacity decreased by 57.14% and SUHI increased by 0.62 °C. Green roofs can play an important role in mitigating this UHI effect.

Pavements constitute a substantial portion of urban spaces and play a significant role in the formation of heat islands within cities. Cool pavements (CP) can keep surface temperatures lower compared to traditional pavements, thereby helping alleviate urban overheating. Additionally, cool pavements utilize evaporative cooling and convert heat into alternative forms of energy to further decrease their overall heat gain (Kousis and Pisello, 2023) and appears to be one of the most important proposed mitigation solutions. In Dhaka city, where pavement construction is on the rise, adopting cool pavements can help reduce the impact of the UHI effect.

Green walls, also known as vertical greening systems, enhance air quality and aesthetics by extracting CO₂ and reducing temperatures both indoors and outdoors. They prove highly effective in densely populated urban areas (Thomas et al., 2023). In Dhaka, where space constraints limit the use of other Urban Green Infrastructure (UGI), green walls can be a highly effective solution to enhance heat mitigation capacity.

Overall, the study identified a robust negative association between LST and HMI changes from 2000 to 2020 across the entire study area. This implies that the conversion of natural to artificial land use has led to a reduction in HMI values. Additionally, the transformation of water bodies and vegetation cover into other Land Use and Land Cover (LULC) types was observed to predominantly decrease HMI in Dhaka city, Bangladesh.

Chapter 7

Conclusion and Recommendations

7.1 Highlights of Results

This thesis assessed the condition of ecosystem services and the varying impacts of urbanization on them. The results are detailed in chapters three, four, five, and six. The main conclusions, based on the key findings from these studies, are summarized as follows:

7.1.1 Chapter 3: Spatiotemporal Horizontal Expansion of Dhaka City, Bangladesh

This study utilized geospatial technologies to analyze the spatiotemporal horizontal expansion of Dhaka city from 2000 to 2021. By employing multitemporal satellite images with spectral signature-based indices, the research classified five major Land Use and Land Cover (LULC) types: waterbodies, vegetation cover, built-up areas, agricultural land, and bare land. The findings revealed a significant increase in built-up areas by 94.94%, while waterbodies experienced a substantial decrease of 70.93%. Bare land initially increased until 2018, after which it decreased due to conversion to built-up areas. Agricultural land decreased by 60.08%, particularly in rural-urban fringe areas. The study highlighted notable changes among the LULC classes, with bare land experiencing the highest conversion rate at 48.94% of its total area. Between 2000 and 2021, 16.80% of agricultural land, 21.64% of vegetation cover, and 12.63% of waterbodies were converted to built-up areas. Agricultural land experienced the highest transition in 2000, with 1,255.13 hectares converted. Overall, waterbodies decreased by 70.93%, primarily due to conversion to other land classes. This information is valuable for policymakers and urban planners in developing sustainable urban management strategies and contributes to achieving Sustainable Development Goals.

7.1.2 Chapter 4: Assessing the Regional Value of Ecosystem Services (ESV) and their Trade-offs in Dhaka City, Bangladesh

This study categorized land use and land cover (LULC) classes in Dhaka city based on the Common International Classification of Ecosystem Services (CICES) framework. The ecosystem service values were globally aligned and adjusted using regional correction factors, leading to the development of region-specific coefficients for the study area. This research is likely the first to estimate ecosystem service (ES) loss in Dhaka using regional coefficient values. Using zonal statistics in GIS, the study calculated region-wise mean values of ecosystem service value (ESV), revealing the highest mean value in the rural-urban fringe area in 2000 (36.12%) and the lowest in the NI area (11.29%). Over the study period, ESV significantly decreased, particularly in the rural-urban fringe area (-87.95%) and other urban zones. The conversion of waterbodies to other land use types resulted in an ESV loss of \$273 million, representing more than half of the total net decline in ESV. The rural-urban fringe areas experienced the highest ES loss (-87.95%), while the new industrial area showed the lowest loss (-66.91%).

The study found ESV losses across all ES types, including provisioning (-71.59%), regulating (-69.44%), and cultural services (-62.45%). This loss could increase the city's vulnerability to issues like flooding, waste assimilation, and pollution, leading to long-term environmental degradation.

The most synergistic relationship between provisioning and regulating ES trade-offs was observed in agricultural areas ($R^2 = 0.97$), followed by waterbodies ($R^2 = 0.74$) and vegetation cover ($R^2 = 0.68$). For regulating vs. cultural ES trade-offs, built-up regions exhibited the highest R^2 value (0.99) due to their aesthetic value, followed by vegetation cover ($R^2 = 0.98$) and waterbodies ($R^2 = 0.93$). No significant relationship was identified in bare land and agricultural land between these ES types. In provisioning vs. cultural ES trade-offs, the strongest relationship was found in waterbody areas ($R^2 = 0.90$), followed by vegetation cover ($R^2 = 0.78$), with no significant relationship identified in bare land areas.

The results provide valuable insights for land administrators, planners, and environmentalists in formulating specific land management strategies. They also aid decision-makers, planners, and stakeholders in promoting sustainable urban development and conserving natural resources.

7.1.3 Chapter 5: Investigating the spatiotemporal patterns of the degree of urbanization and their relationship with ecosystem service values

This study utilized the Digital Building Height Model to calculate the vertical profile of the city, revealing that the most significant urban development occurred in the northwest and middle east parts of the study area. These vertical profile datasets were then used to measure the degree of urbanization through technomass, a three-dimensional indicator encompassing human-made material stocks such as buildings and infrastructure. The volumes and rates of technomass showed positive trends both spatially and temporally, varying significantly across the study area—from 6,213.52 m³/ha (the lowest in 2000 in the fringe area) to 105,432.15 m³/ha (the highest in 2021 in the OCBD region).

A Geographically Weighted Regression (GWR) model was employed to analyze geographic spatial relationships between urbanization indicators (nighttime light data (NTL), population density (PD), and technomass) and changes in ecosystem service value (ESV). The local R^2 values, ranging from 0 to 1, indicated that technomass was the most suitable indicator for analyzing urbanization's impact on ESV ($r > 0.61$), followed by NTL ($r > 0.56$) and PD ($r > 0.54$). Pearson's correlation analysis revealed a significant negative correlation ($p < 0.01$) between ESV and the urbanization indicators. Technomass exhibited a strong negative association with ESV ($r > -0.96$), followed by PD ($r > -0.94$) and NTL ($r > -0.60$). Additionally, there was a significant positive correlation between technomass and NTL/PD, while the correlation between technomass/NTL/PD and ESV was negative.

The study found that areas with higher urbanization levels experienced a significant decline in ESV. The highest rate of ESV decline (87.55%) was observed where urbanization intensified, with a net ESV decrease of 68.34% and a technomass increase of 243.11% throughout the study period. Bivariate Local Indicators of Spatial Association (LISA)

cluster maps indicated that areas with high urbanization levels corresponded with very low ESV values.

This study highlights the effectiveness of using technomass analysis techniques to understand the spatiotemporal dynamic evolution of the relationship between urbanization and ESV. It suggests that the government should focus on various aspects of urbanization and selectively promote ecological protection, restoration, and construction within the identified spatial clustering areas.

7.1.4 Chapter 6: Evaluating the Cooling Potential of Ecosystem Services in Dhaka City, Bangladesh, for Nature-Based Mitigation of Urban Heat Islands Resulting from Urbanization

The urban thermal environment in Dhaka city has been significantly impacted by rising urbanization and population growth. This study examined the spatiotemporal Surface Urban Heat Island (SUHI) phenomenon and evaluated the urban heat mitigation potential of ecosystem services using the InVEST Urban Cooling Model. Findings indicated that SUHI values in Dhaka are closely related to Land Use and Land Cover (LULC) classifications. Areas with the lowest SUHI values, primarily located around the urban fringe with abundant water, vegetation cover, and larger urban vegetation cover, showed greater cooling. Intermediate SUHI values were found in the NI and NCBD areas, characterized by grasslands and water bodies. Conversely, the urban core, with minimal vegetation cover, exhibited the highest SUHI values. The OCBD region had the highest SUHI intensity of 8.37°C in 2012, while the lowest SUHI of 1.18°C was recorded in the NI region in 2020 due to reduced commercial activity.

Over the study period, the mean SUHI increased in all LULC classes, with notable rises in built-up and bare soil areas, from 2.75°C to 3.24°C and 1.12°C to 1.47°C, respectively, between 2000 and 2018. However, a significant reduction in SUHI values occurred in 2020 due to decreased commercial activities during the COVID-19 pandemic, with built-up areas dropping from 2.75°C to 1.01°C and bare soil from 1.12°C to 0.52°C.

The InVEST UCM model was used to calculate the temporal changes in heat mitigation scenarios for Dhaka city, with the Cooling effects index ranging from zero to one (higher values indicating greater Cooling effects). Results showed a decrease in the average Cooling effects index from 0.57 to 0.30 between 2000 and 2020, reflecting a 47.55% reduction. Using GIS zonal statistics, the study found the highest heat mitigation index (HMI) in the rural-urban fringe area (69.85%) in 2000, and the lowest in the new industrial area (20.36%). Over the study period, the new industrial area experienced the most significant HMI decrease (-64.58%), followed by OCBD (-62.42%), fringe areas (-44.37%), NCBD (-33.22%), and the inner city (-28.44%).

The study highlighted that the conversion of vegetation cover to other land uses significantly reduced heat mitigation capacity, especially in fringe areas and newly developed central business districts (CBD). Regions with higher HMI were mostly found in areas with better hydrological conditions and vegetation cover. Pearson's correlation analysis showed a significant negative correlation ($p < 0.01$) between Land Surface Temperature (LST) and HMI ($r = -0.77$). The rural-urban fringe area exhibited the strongest negative correlation in HMI changes ($r > -0.70$), followed by the inner city ($r > -0.61$), NCBD ($r > -0.46$), OCBD ($r > -0.40$), and the NI region ($r > -0.06$).

Overall, the study identified a robust negative association between LST and HMI changes from 2000 to 2020 across the entire study area, indicating that the conversion of natural land to artificial uses has reduced HMI values. The transformation of water bodies and vegetation cover into other LULC types mainly decreased HMI in Dhaka city, Bangladesh.

7.2 Recommendations

The study's findings revealed that Dhaka's environmental quality is gradually decreasing and losing its liveability. Therefore, some specific recommendations are proposed for the city to respond to this situation based on the results.

7.2.1 Prioritize Conservation and Restoration of Waterbodies

- Implement strict zoning laws to protect remaining waterbodies, as their decrease by 70.93%, reflects a critical loss of natural resources. Establishing policies that penalize the conversion of waterbodies can help preserve these ecosystems. This conservation should focus on areas where waterbodies were converted to built-up zones, particularly in high-ESV regions like the rural-urban fringe.

7.2.2 Expand Green Infrastructure and Preserve Vegetation Cover in Urban Planning

- Enhance vegetation cover in developed and high-density OCBD, NCBD, NI areas to reduce land surface temperatures (LST). Urban vegetation cover can help reverse the noted decline in the cooling effects index, which dropped from 0.57 to 0.30.
- Incorporate green roofs and vertical gardens in new constructions, particularly in areas with high technomass, where a 243.11% increase was recorded over the study period, leading to higher urban heat and ESV loss.

7.2.3 Encourage Compact, Vertical Urban Development

- Promote high-density, vertical development to address and reduce the additional land conversion, particularly in zones like OCBD, where technomass values peaked. Compact urban design can help reduce the expansion into high-ESV regions like the rural-urban fringe.
- Redevelop underutilized areas in the inner city region to reduce pressure on agricultural and vegetation cover, which have been heavily converted to built-up areas (16.80% of agricultural and 21.64% of vegetation cover converted). This approach reduces habitat loss and preserves essential ecosystem services.

7.2.4 Strengthen Policy Framework for Ecosystem Service Valuation (ESV)

- Integrate ESV data into land-use policies to highlight and preserve areas with high ecosystem service value in agricultural land, vegetation cover and waterbodies. By valuing ecosystem services explicitly, urban planners can prioritize zones for conservation or limited development.
- Use region-specific coefficients, as developed in this study, to guide decision-making on land conversion and optimize urban growth with minimum ESV impact. This can help reduce the extensive ESV losses observed in the rural-urban fringe (-87.95%) and urban core zones.

7.2.5 Utilizing Technomass for Monitoring Urban Growth

- Technomass can be a key indicator for tracking urbanization growth, showing strong negative correlations (technomass $r > -0.96$) with ESV in high-density regions. Frequent monitoring can help assess areas where urban growth directly impacts ecosystem services.

7.2.6 Implement Urban Heat Mitigation Measures in High SUHI Zones

- Enhance vegetation cover and water features in areas with high SUHI values, particularly the urban core, where SUHI value reached 8.37°C. Urban cooling interventions are critical, as high-density and low-green zones like OCBD and NI observed the lowest cooling effects and the greatest decline in the heat mitigation index.
- Target fringe and central business districts for heat mitigation measures, as these areas observed a 47.55% reduction in cooling effects. Increasing vegetation cover and managing land surface temperature through water bodies and vegetation cover can counterbalance the higher SUHI intensities.

By following these recommendations, Dhaka City can achieve sustainable urban management, enhance ecosystem services, and mitigate the adverse effects of urbanization.

7.3 Limitations and Future Scope

There are some limitations of the research, which should be improved in future research. Vertical growth analysis of this research relied on the availability of DEM images at that time. Other types of DEM images like LIDAR-based DEM, and Copernicus DEM could be explored to identify vertical growth. This research used Landsat data with a 30m spatial resolution for LULC classification, but UAV data or other finer-resolution images could provide better results. Calculating ESV from a continuous raster can provide better results but for the proper planning of Dhaka city, this research used the administrative boundary. This research modified the global value coefficient for ESV calculation by incorporating regional parameters such as NPP, NDVI, Yield, Rainfall, FVC, and NPP/NDVI, but other factors like temperature, and socio-economic data could be explored for future improvements.

Appendices

Appendix A

Table A1 Correction factors used for adjusting the model parameters

Correction factors used for adjusting the model parameters							
	Fn4			Fn2	Fn3		Fn1
Year	Yield	NPP	NDVI	Rainfall	FVC	NPP & NDVI	Bi
2000	2.39	0.65	0.74	0.93	0.85	0.69	1.39
2007	1.82	0.65	0.69	1.08	0.84	0.67	1.34
2009	1.65	0.65	0.69	0.90	0.82	0.67	1.33
2012	1.72	0.69	0.63	0.60	0.75	0.66	1.32
2018	2.29	0.71	0.63	0.81	0.64	0.67	1.34
2021	1.86	0.74	0.63	0.91	0.64	0.69	1.38

Table A1 Regional Modified Coefficient for 2000 Ecosystem Service Value Calculation

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0.00	25.85	238.93	0.11	0.00
2	CR	Fn1	Climate Regulation	876.59	3671.63	321.88	0.00	64.66
3	DR	Fn1	Disturbance regulation	5363.73	118.55	0.00	0.00	0.00
4	NC	Fn1	Nutrient Cycling	3077.06	5.39	0.00	0.00	0.00
5	WT	Fn1	Waste Treatment	5751.74	10.77	461.26	0.00	0.00
6	Po	Fn1	Pollination	0.00	53.89	0.00	0.00	0.00
7	BC	Fn1	Biological Control	1702.89	19.77	338.48	0.00	0.00
8	Ha	Fn1	Habitat/Refugia	631.76	0.00	0.00	0.00	0.00
9	RM	Fn1	Raw Materials	763.43	150.88	129.41	0.00	0.00
10	GR	Fn1	Genetic Resources	2098.08	41.31	0.00	0.00	0.00
11	Re	Fn1	Recreation	7862.38	1557.38	0.00	0.00	0.00
12	Cu	Fn1	Cultural	2320.81	7.05	0.00	0.00	404.17
13	WR	Fn2	Water Regulation	2663.27	32.45	170.95	0.00	0.00
14	WS	Fn2	Water Supply	6737.51	411.03	0.00	0.00	0.00
15	EC	Fn3	Erosion Control	2863.67	16.47	0.00	0.00	0.00
16	SF	Fn3	Soil Formation	0.00	3.96	298.30	0.00	0.00
17	Fp	Fn4	Food Production	2223.80	617.72	570.56	0.00	0.00

Table A2 Regional Modified Coefficient for 2007 Ecosystem Service Value Calculation

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0.00	24.92	230.33	0.11	0.00
2	CR	Fn1	Climate Regulation Disturbance	845.06	3539.56	310.30	0.00	62.34
3	DR	Fn1	regulation	5170.79	114.29	0.00	0.00	0.00
8	NC	Fn1	Nutrient Cycling	2966.37	5.20	0.00	0.00	0.00
9	WT	Fn1	Waste Treatment	5544.84	10.39	444.67	0.00	0.00
10	Po	Fn1	Pollination	0.00	51.95	0.00	0.00	0.00
11	BC	Fn1	Biological Control	1641.63	19.05	326.30	0.00	0.00
12	Ha	Fn1	Habitat/Refugia	609.03	0.00	0.00	0.00	0.00
14	RM	Fn1	Raw Materials	735.97	145.46	124.75	0.00	0.00
15	GR	Fn1	Genetic Resources	2022.61	39.82	0.00	0.00	0.00
16	Re	Fn1	Recreation	7579.56	1501.36	0.00	0.00	0.00
17	Cu	Fn1	Cultural	2237.33	6.79	0.00	0.00	389.63
4	WR	Fn2	Water Regulation	7824.20	477.33	0.00	0.00	0.00
5	WS	Fn2	Water Supply	3638.54	20.93	0.00	0.00	0.00
6	EC	Fn3	Erosion Control	2829.98	16.28	0.00	0.00	0.00
7	SF	Fn3	Soil Formation	0.00	3.91	294.79	0.00	0.00
13	Fp	Fn4	Food Production	1693.44	470.40	434.49	0.00	0.00

Table A3 Regional Modified Coefficient for 2009 Ecosystem Service Value Calculation

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0.00	24.74	228.61	0.11	0.00
2	CR	Fn1	Climate Regulation	838.75	3513.14	307.99	0.00	61.87
3	DR	Fn1	Disturbance regulation	5132.20	113.44	0.00	0.00	0.00
8	NC	Fn1	Nutrient Cycling	2944.23	5.16	0.00	0.00	0.00
9	WT	Fn1	Waste Treatment	5503.46	10.31	441.35	0.00	0.00
10	Po	Fn1	Pollination	0.00	51.56	0.00	0.00	0.00
11	BC	Fn1	Biological Control	1629.38	18.91	323.87	0.00	0.00
12	Ha	Fn1	Habitat/Refugia	604.49	0.00	0.00	0.00	0.00
14	RM	Fn1	Raw Materials	730.48	144.37	123.82	0.00	0.00
15	GR	Fn1	Genetic Resources	2007.52	39.53	0.00	0.00	0.00
16	Re	Fn1	Recreation	7523.00	1490.16	0.00	0.00	0.00
17	Cu	Fn1	Cultural	2220.63	6.74	0.00	0.00	386.72
4	WR	Fn2	Water Regulation	2577.36	31.40	165.44	0.00	0.00
5	WS	Fn2	Water Supply	6520.17	397.77	0.00	0.00	0.00
6	EC	Fn3	Erosion Control	2762.60	15.89	0.00	0.00	0.00
7	SF	Fn3	Soil Formation	0.00	3.82	287.77	0.00	0.00
13	Fp	Fn4	Food Production	1535.26	426.46	393.90	0.00	0.00

Table A4 Regional Modified Coefficient for 2012 Ecosystem Service Value Calculation

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0.00	24.55	226.89	0.11	0.00
2	CR	Fn1	Climate Regulation	832.44	3486.73	305.67	0.00	61.41
3	DR	Fn1	Disturbance regulation	5093.62	112.58	0.00	0.00	0.00
8	NC	Fn1	Nutrient Cycling	2922.10	5.12	0.00	0.00	0.00
9	WT	Fn1	Waste Treatment	5462.08	10.23	438.03	0.00	0.00
10	Po	Fn1	Pollination	0.00	51.18	0.00	0.00	0.00
11	BC	Fn1	Biological Control	1617.13	18.77	321.43	0.00	0.00
12	Ha	Fn1	Habitat/Refugia	599.94	0.00	0.00	0.00	0.00
14	RM	Fn1	Raw Materials	724.98	143.29	122.89	0.00	0.00
15	GR	Fn1	Genetic Resources	1992.42	39.23	0.00	0.00	0.00
16	Re	Fn1	Recreation	7466.43	1478.95	0.00	0.00	0.00
17	Cu	Fn1	Cultural	2203.94	6.69	0.00	0.00	383.82
4	WR	Fn2	Water Regulation	1718.24	20.93	110.29	0.00	0.00
5	WS	Fn2	Water Supply	4346.78	265.18	0.00	0.00	0.00
6	EC	Fn3	Erosion Control	2526.77	14.54	0.00	0.00	0.00
7	SF	Fn3	Soil Formation	0.00	3.50	263.21	0.00	0.00
13	Fp	Fn4	Food Production	1600.39	444.55	410.62	0.00	0.00

Table A5 Regional Modified Coefficient for 2018 Ecosystem Service Value Calculation

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0.00	24.92	230.33	0.11	0.00
2	CR	Fn1	Climate Regulation	845.06	3539.56	310.30	0.00	62.34
3	DR	Fn1	Disturbance regulation	5170.79	114.29	0.00	0.00	0.00
8	NC	Fn1	Nutrient Cycling	2966.37	5.20	0.00	0.00	0.00
9	WT	Fn1	Waste Treatment	5544.84	10.39	444.67	0.00	0.00
10	Po	Fn1	Pollination	0.00	51.95	0.00	0.00	0.00
11	BC	Fn1	Biological Control	1641.63	19.05	326.30	0.00	0.00
12	Ha	Fn1	Habitat/Refugia	609.03	0.00	0.00	0.00	0.00
14	RM	Fn1	Raw Materials	735.97	145.46	124.75	0.00	0.00
15	GR	Fn1	Genetic Resources	2022.61	39.82	0.00	0.00	0.00
16	Re	Fn1	Recreation	7579.56	1501.36	0.00	0.00	0.00
17	Cu	Fn1	Cultural	2237.33	6.79	0.00	0.00	389.63
4	WR	Fn2	Water Regulation	2319.62	28.26	148.89	0.00	0.00
5	WS	Fn2	Water Supply	5868.15	358.00	0.00	0.00	0.00
6	EC	Fn3	Erosion Control	2156.17	12.40	0.00	0.00	0.00
7	SF	Fn3	Soil Formation	0.00	2.98	224.60	0.00	0.00
13	Fp	Fn4	Food Production	2130.75	591.87	546.69	0.00	0.00

Table A6 Regional Modified Coefficient for 2021 Ecosystem Service Value Calculation

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0.00	25.67	237.21	0.11	0.00
2	CR	Fn1	Climate Regulation	870.28	3645.21	319.57	0.00	64.20
3	DR	Fn1	Disturbance regulation	5325.14	117.70	0.00	0.00	0.00
8	NC	Fn1	Nutrient Cycling	3054.92	5.35	0.00	0.00	0.00
9	WT	Fn1	Waste Treatment	5710.36	10.70	457.94	0.00	0.00
10	Po	Fn1	Pollination	0.00	53.50	0.00	0.00	0.00
11	BC	Fn1	Biological Control	1690.64	19.62	336.04	0.00	0.00
12	Ha	Fn1	Habitat/Refugia	627.21	0.00	0.00	0.00	0.00
14	RM	Fn1	Raw Materials	757.94	149.80	128.48	0.00	0.00
15	GR	Fn1	Genetic Resources	2082.99	41.01	0.00	0.00	0.00
16	Re	Fn1	Recreation	7805.82	1546.18	0.00	0.00	0.00
17	Cu	Fn1	Cultural	2304.12	7.00	0.00	0.00	401.26
4	WR	Fn2	Water Regulation	2605.99	31.75	167.28	0.00	0.00
5	WS	Fn2	Water Supply	6592.61	402.19	0.00	0.00	0.00
6	EC	Fn3	Erosion Control	2156.17	12.40	0.00	0.00	0.00
7	SF	Fn3	Soil Formation	0.00	2.98	224.60	0.00	0.00
13	Fp	Fn4	Food Production	1730.66	480.74	444.04	0.00	0.00

Appendix B

Table B1: Total value of Ecosystem Services (ESV) by land use type in 2000 (Million USD)

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	0	161319.394	1389313.301	231.6685	0
2	CR	Fn1	Climate Regulation	5822237.996	22909608.95	1871681.198	0	623556.313
3	DR	Fn1	Disturbance regulation	35625478.85	739727.4794	0	0	0
4	NC	Fn1	Nutrient Cycling	20437565.77	33651.57252	0	0	0
5	WT	Fn1	Waste Treatment	38202574.36	67216.41418	2682120.692	0	0
6	Po	Fn1	Pollination	0	336255.5326	0	0	0
7	BC	Fn1	Biological Control	11310452.51	123331.2787	1968187.108	0	0
8	Ha	Fn1	Habitat/Refugia	4196066.17	0	0	0	0
9	RM	Fn1	Raw Materials	5070638.993	941463.4527	752487.4532	0	0
10	GR	Fn1	Genetic Resources	13935278.85	257764.107	0	0	0
11	Re	Fn1	Recreation	52221312.92	9717498.68	0	0	0
12	Cu	Fn1	Cultural	15414657.6	31049.64681	0	0	3897495.037
13	WR	Fn2	Water Regulation	17689218.97	202461.6424	994055.1785	0	0
14	WS	Fn2	Water Supply	44749975.19	2564688.222	0	0	0
15	EC	Fn3	Erosion Control	19020247.12	102785.425	0	0	0
16	SF	Fn3	Soil Formation	0	24715.17443	1734549.025	0	0
17	Fp	Fn4	Food Production	14770297.71	3854340.5	3317719.618	0	0

Table B2: Total value of Ecosystem Services (ESV) by land use type in 2007 (Million USD)

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	1537816.119	131278.6958	1094476.022	524.4278	0
2	CR	Fn1	Climate Regulation	4075509.991	18643409.89	1474476.773	0	666331.1459
3	DR	Fn1	Disturbance regulation	24937488.83	601976.3424	0	0	0
4	NC	Fn1	Nutrient Cycling	14306097.33	27385.01827	0	0	0
5	WT	Fn1	Waste Treatment	26741430.63	54699.4566	2112926.425	0	0
6	Po	Fn1	Pollination	0	273638.4429	159500.9852	0	0
7	BC	Fn1	Biological Control	7917206.79	100364.6804	1550502.392	0	0
8	Ha	Fn1	Habitat/Refugia	2937205.523	0	0	0	0
9	RM	Fn1	Raw Materials	3549397.996	766145.2921	592796.0769	0	0
10	GR	Fn1	Genetic Resources	9754559.71	209763.5936	0	0	0
11	Re	Fn1	Recreation	36554411.32	7907918.086	0	0	0
12	Cu	Fn1	Cultural	10790110.45	25267.61995	0	0	4164856.133
13	WR	Fn2	Water Regulation	37734240.72	2514160.842	0	0	0
14	WS	Fn2	Water Supply	17547812.89	110243.7657	0	0	0
15	EC	Fn3	Erosion Control	13648298.91	85745.15107	0	0	0
16	SF	Fn3	Soil Formation	0	20617.7711	1400757.638	0	0
17	Fp	Fn4	Food Production	8167041.191	2477657.316	2064568.17	0	0

Table B3: Total value of Ecosystem Services (ESV) by land use type in 2009 (Million USD)

Sl	Ecosystem Function			Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	1476189.381	114186.8973	872110.9705	805.7555	0
2	CR	Fn1	Climate Regulation	3912187.222	16216135.58	1174906.844	0	704117.9882
3	DR	Fn1	Disturbance regulation	23938139.12	523602.1758	0	0	0
4	NC	Fn1	Nutrient Cycling	13732792.05	23819.63234	0	0	0
5	WT	Fn1	Waste Treatment	25669789.41	47577.87388	1683642.472	0	0
6	Po	Fn1	Pollination	0	238012.151	127095.1179	0	0
7	BC	Fn1	Biological Control	7599931.127	87297.72471	1235486.313	0	0
8	Ha	Fn1	Habitat/Refugia	2819499.386	0	0	0	0
9	RM	Fn1	Raw Materials	3407158.74	666397.1883	472357.5039	0	0
10	GR	Fn1	Genetic Resources	9363653.614	182453.4725	0	0	0
11	Re	Fn1	Recreation	35089522.84	6878348.574	0	0	0
12	Cu	Fn1	Cultural	10357705.5	21977.90819	0	0	4401040.142
13	WR	Fn2	Water Regulation	12021566.26	144942.3059	631109.5736	0	0
14	WS	Fn2	Water Supply	30412014.94	1836060.502	0	0	0
15	EC	Fn3	Erosion Control	12885578.39	73353.24186	0	0	0
16	SF	Fn3	Soil Formation	0	17638.08602	0	0	0
17	Fp	Fn4	Food Production	7160908.554	1968470.775	1502659.009	0	0

Table B4: Total value of Ecosystem Services (ESV) by land use type in 2012 (Million USD)

				Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up- Area
1	GR	Fn1	Gas Regulation	1182177	72156.11832	707065.4584	652.379	0
2	CR	Fn1	Climate Regulation Disturbance	3132997.6	10247177.44	952557.7299	0	885865.92
3	DR	Fn1	regulation	19170384	330870.7167	0	0	0
4	NC	Fn1	Nutrient Cycling	10997634	15051.92146	0	0	0
5	WT	Fn1	Waste Treatment	20557142	30065.0493	1365016.009	0	0
6	Po	Fn1	Pollination	0	150402.8337	103042.5838	0	0
7	BC	Fn1	Biological Control	6086254.2	55164.51626	1001672.638	0	0
8	Ha	Fn1	Habitat/Refugia	2257940.2	0	0	0	0
9	RM	Fn1	Raw Materials	2728555.5	421104.6583	382964.6528	0	0
10	GR	Fn1	Genetic Resources	7498696.4	115294.6149	0	0	0
11	Re	Fn1	Recreation	28100749	4346513.876	0	0	0
12	Cu	Fn1	Cultural	8294763.1	13888.1131	0	0	5537042.85
13	WR	Fn2	Water Regulation	6466777.7	61523.14194	343699.6508	0	0
14	WS	Fn2	Water Supply	16359577	779346.0316	0	0	0
15	EC	Fn3	Erosion Control	9509758	42717.05685	0	0	0
16	SF	Fn3	Soil Formation	0	10271.49045	820217.8454	0	0
17	Fp	Fn4	Food Production	6023248.3	1306495.967	1279589.076	0	0

Table B5: Total value of Ecosystem Services (ESV) by land use type in 2018 (Million USD)

				Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	724196.61	63389.45844	628188.4033	829.688	0
2	CR	Fn1	Climate Regulation	1919261	9002189.188	846294.6568	0	954234.28
3	DR	Fn1	Disturbance regulation	11743696	290671.3393	0	0	0
4	NC	Fn1	Nutrient Cycling	6737104.1	13223.17735	0	0	0
5	WT	Fn1	Waste Treatment	12593218	26412.27435	1212740.938	0	0
6	Po	Fn1	Pollination	0	132129.5325	91547.61477	0	0
7	BC	Fn1	Biological Control	3728413.5	48462.26339	889930.5259	0	0
8	Ha	Fn1	Habitat/Refugia	1383204.6	0	0	0	0
9	RM	Fn1	Raw Materials	1671501.5	369942.2427	340242.8317	0	0
10	GR	Fn1	Genetic Resources	4593669.6	101286.8121	0	0	0
11	Re	Fn1	Recreation	17214399	3818431.023	0	0	0
12	Cu	Fn1	Cultural	5081336.7	12200.76673	0	0	5964374.5
13	WR	Fn2	Water Regulation	5268231.1	71876.22958	406080.6406	0	0
14	WS	Fn2	Water Supply	13327508	910494.0438	0	0	0
15	EC	Fn3	Erosion Control	4897013.4	31545.18259	0	0	0
16	SF	Fn3	Soil Formation	0	7585.167744	612558.1897	0	0
17	Fp	Fn4	Food Production	4839281.9	1505317.537	1490997.74	0	0

Table B6: Total value of Ecosystem Services (ESV) by land use type in 2021 (Million USD)

				Waterbody	Vegetation cover	Agricultural Land	Bare Land	Built-up-Area
1	GR	Fn1	Gas Regulation	650993.31	49286.4102	592742.9664	588.985	0
2	CR	Fn1	Climate Regulation	1725258.1	6999359.198	798542.6071	0	1199627.17
3	DR	Fn1	Disturbance regulation	10556619	226002.039	0	0	0
4	NC	Fn1	Nutrient Cycling	6056103.6	10281.25116	0	0	0
5	WT	Fn1	Waste Treatment	11320269	20536.00425	1144312.211	0	0
6	Po	Fn1	Pollination	0	102733.0174	86382.05427	0	0
7	BC	Fn1	Biological Control	3351537.7	37680.25554	839716.3288	0	0
8	Ha	Fn1	Habitat/Refugia	1243387.4	0	0	0	0
9	RM	Fn1	Raw Materials	1502542.7	287636.5499	321044.6807	0	0
10	GR	Fn1	Genetic Resources	4129331.9	78752.26404	0	0	0
11	Re	Fn1	Recreation	15474332	2968896.759	0	0	0
12	Cu	Fn1	Cultural	4567704.6	9486.30906	0	0	7498185.55
13	WR	Fn2	Water Regulation	5166149.2	60964.57049	417994.7868	0	0
14	WS	Fn2	Water Supply	13069263	772270.3129	0	0	0
15	EC	Fn3	Erosion Control	4274418.5	23816.00448	0	0	0
16	SF	Fn3	Soil Formation	0	5726.65536	561241.2161	0	0
17	Fp	Fn4	Food Production	3430869	923084.4623	1109574.976	0	0

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