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Spatiotemporal analysis and urbanization trajectories of private economic zones in Bangladesh using remote sensing

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SPATIOTEMPORAL ANALYSIS AND URBANIZATION TRAJECTORIES OF PRIVATE ECONOMIC ZONES IN BANGLADESH USING REMOTE SENSING

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Abstract

Private Economic Zones (PEZs) are important instruments of industrial development in Bangladesh, yet systematic evidence on their internal physical development trajectories remains limited. This study develops a multi-source remote-sensing framework to quantify and compare the spatiotemporal development of twelve Private Economic Zones from 2018 to 2025 using their exact, manually verified zero-offset boundaries as fixed analytical units. Annual high-resolution optical imagery derived from Sentinel-2 through the Gamma S2DR4 super-resolution workflow was used to generate 2-m LULC products, while VIIRS VNP46A3 nighttime-light radiance and 100-m WorldPop population data provided complementary measures of anthropogenic and demographic intensity. The datasets were harmonized through a common 100-m master grid using dataset-specific aggregation procedures, with LULC represented by five classes: built-up, farmland, water, forest, and meadow. Zone-level statistics were subsequently used to construct three complementary development measures: the Normalized Urbanization Index (NUI), the Equally Weighted Core Urbanization Index (ECUI), and the Normalized LULC Dynamics Index (NLDI). To identify distinct longitudinal development patterns, the index trajectories were further grouped using K-Means clustering with $k = 4$. The results demonstrate substantial heterogeneity among the twelve zones rather than a uniform development pathway. The Meghna, City, and East West Special Economic Zones consistently occupy the highest-development group across the three indices, reflecting strong levels of built-up development together with elevated nighttime-light and population signals. In contrast, Hossaindi Economic Zone exhibits the most pronounced transformation, with NUI increasing from 0.1595 in 2018 to 0.7921 in 2025, ECUI from 0.1527 to 0.6005, and NLDI from 0.0979 to 0.8647. The lowest-development group remains comparatively stable at low index levels, although Kishoreganj and Cumilla show measurable late-period increases. Comparison of the three indices further demonstrates that physical land transformation can progress at a different rate from the corresponding luminous and demographic signals, highlighting the value of a multidimensional assessment rather than reliance on a single indicator. Overall, the study provides a reproducible, spatially consistent baseline for monitoring internal PEZ development in Bangladesh and establishes a foundation for future investigation of surrounding urbanization and regional spillover using the already prepared buffer, administrative, and Upazila Group (UG) spatial framework.

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1. Introduction

1.1 Background and Research Context

Bangladesh is undergoing rapid urban and industrial transformation, and the spatial consequences of this transformation are not confined to established urban centers. The expansion of industrial estates and economic zones can convert agricultural land, vegetation, wetlands, water bodies, and other open areas into factories, roads, utilities, storage facilities, worker settlements, and associated commercial infrastructure. These changes are important because the physical transformation of land provides a direct spatial indication of whether a planned industrial development is progressing toward actual build-out. Remote sensing therefore offers an important means of monitoring economic-zone development repeatedly and consistently, particularly where conventional economic or administrative statistics do not provide sufficiently fine spatial detail. Research in Gazipur, one of Bangladesh’s major industrial and rapidly urbanizing areas, has already demonstrated that urban expansion can produce substantial changes in agricultural and other land-cover classes and that the resulting spatial transformation is strongly associated with demographic, economic, and accessibility-related factors [1, 2]. These findings provide a strong basis for examining industrial development through LULC change, but they do not directly answer how individual Private Economic Zones themselves are changing within their formal boundaries.

LULC studies generally use multi-temporal satellite observations to characterize the physical composition of a landscape and to measure how that composition changes over time. A typical workflow consists of defining the spatial and temporal study framework, acquiring comparable satellite scenes, preparing and validating the imagery, classifying land-cover categories, extracting spatial statistics, and comparing the results across years. Depending on the scale and purpose of the study, classification can be performed using supervised statistical classifiers, machine-learning models, or deep-learning semantic-segmentation architectures. The resulting class maps can then be analyzed using pixel counts, areal percentages, transition matrices, or other change indicators. In rapidly changing areas, the spatial resolution of the input imagery is particularly important because buildings, narrow roads, small water bodies, fragmented vegetation, and mixed agricultural or peri-urban surfaces may be smaller than the native pixel size of medium-resolution sensors.

This issue is particularly relevant to Bangladesh. The Bangladesh Open LULC Map (BOLM) provides high-resolution pixel-level LULC annotations for approximately 4392 km² of the Dhaka metropolitan region and surrounding areas using high-resolution Bing imagery. The BOLM study demonstrated that high-resolution RGB imagery can provide substantially stronger fine-scale segmentation performance than lower-resolution Sentinel-2 configurations, while also emphasizing the complementary value of multispectral Sentinel-2 data for spectral and temporal analysis [3]. The BOLM framework is therefore important to the present study because the present work builds on the same broader high-resolution LULC context while addressing the additional requirement of obtaining a repeated time

series for individual economic zones. Instead of relying only on irregularly updated commercial RGB imagery, the present study uses Sentinel-2 as the temporal source and employs the Gamma Earth S2DR4 super-resolution framework to generate a finer-resolution RGB analytical product suitable for the previously developed LULC workflow [4, 5].

LULC, however, represents only the physical surface. Urban and industrial development also changes patterns of human activity and electricity use, and these dimensions may not always change at the same rate as built-up land. Nighttime Lights (NTL) provide a complementary remotely sensed indicator because artificial illumination is associated with settlement, infrastructure, road networks, electricity use, and human activity. The use of satellite-observed nighttime illumination for urban and socioeconomic analysis is well established, and recent work has highlighted its value for urban applications while also recognizing the need to account for spatial context and sensor characteristics [6]. The present study uses the VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Monthly L3 product (VNP46A3) as the principal NTL data source [7]. In the present study, NTL is not treated as a direct measure of industrial production. Instead, nighttime-light intensity is used as a complementary indicator of development intensity within the fixed boundaries of the economic zones.

Population provides a further dimension of urbanization. Fine-resolution gridded population products allow demographic intensity to be represented spatially and compared with land-cover and nighttime-light observations. In this study, gridded population is used to describe the human presence associated with each economic-zone footprint. Combining population with built-up land and NTL helps distinguish different development situations. A zone may experience substantial construction while population remains comparatively low because workers commute from surrounding settlements, whereas a zone embedded in an established urban corridor may already contain a large population and strong nighttime illumination before additional physical expansion occurs. The resulting interpretation is therefore more informative when multiple spatial indicators are considered together [8].

The Bangladesh literature provides substantial evidence of urban and environmental land-cover change, but much of the work has focused on cities, districts, ecological regions, or the surrounding areas of individual industrial developments. Gazipur studies document extensive built-up expansion and corresponding changes in agricultural, vegetation, and water-related land covers [1, 2]. Research surrounding the Dhaka Export Processing Zone (DEPZ) has examined industrially associated urbanization in the surrounding catchment, including changes in built-up land and population beyond the formal industrial boundary [9]. Other Bangladesh research has examined land-use changes associated with major economic-zone environments and has demonstrated that industrial-zone construction can produce detectable landscape transformation and environmental consequences [10–12]. These findings collectively establish that industrial development can be observed through remote sensing, but the main analytical emphasis has generally remained on broader regional change, single industrial sites, or surrounding catchments.

1.2 Problem Statement

This creates a specific research gap. There remains limited systematic evidence comparing the internal development trajectories of multiple Private Economic Zones in Bangladesh using a common spatial definition, a common annual observation framework, and a common combination of LULC, nighttime lights, and gridded population indicators. In particular, the internal development of a zone is conceptually different from the spillover urbanization of its surrounding area. A zone that remains predominantly agricultural

or otherwise undeveloped is not equivalent to a zone whose internal footprint is already heavily occupied by industrial infrastructure. Understanding this internal maturation is therefore an important first step before assessing wider spillover effects.

The present study consequently shifts the primary unit of observation from the surrounding catchment to the exact footprint of the economic zone itself. Twelve Private Economic Zones are examined from 2018 to 2025 using their zero-offset boundaries. The broader spatial framework developed for the research also contains 1 km, 2 km, 3 km, 4 km, and 5 km buffers and five Upazila Group (UG) Zones. These surrounding spatial units were established to support efficient satellite-data acquisition and future regional spillover analysis, but the empirical results reported in this study are intentionally restricted to the exact economic-zone boundaries. This fixed-boundary strategy ensures that changes through time represent changes within the same physical spatial unit rather than changes caused by a varying analytical area.

1.3 Outcome of the Project

The aim of this study is to assess the land-cover and urbanization trajectories across the twelve Private Economic Zones of Bangladesh using multi-source remotely sensed data. The specific objectives are to: (1) quantify annual changes in five LULC classes, namely farmland, water, forest, built-up, and meadow, within the boundary of each economic zone from 2018 to 2025; (2) quantify nighttime-light intensity and gridded population density for the same spatial units and place the continuous variables on a common normalized scale; (3) construct and compare complementary composite indicators, including a Normalized Urbanization Index (NUI), an Equally Weighted Core Urbanization Index (ECUI), and a Normalized LULC Dynamics Index (NLDI); and (4) identify similarities and differences among the twelve zones based on the level, pace, and shape of their longitudinal development trajectories.

The methodological framework combines high-resolution RGB imagery generated from Sentinel-2 observations using the Gamma Earth S2DR4 super-resolution workflow, VIIRS VNP46A3 nighttime-light observations, and gridded population data. The imagery and derived LULC products are aligned with a common spatial analysis framework, while the NTL and population layers are standardized to a 100 m grid for direct pixel-aligned comparison. Zone-level LULC is summarized through class-specific pixel counts and percentages, while NTL and population are expressed as density measures. These variables are then used to construct complementary indices that capture different aspects of development intensity rather than claiming to measure economic output directly.

The results show that the twelve economic zones do not follow a single trajectory. Several zones show substantial increases in built-up land accompanied by stronger nighttime-light and population signals, whereas other zones remain dominated by farmland, meadow, water, or other non-built land covers. The index comparison also shows that development trajectories can differ depending on whether the metric emphasizes physical land conversion alone or combines physical, luminous, and demographic indicators. These differences provide evidence that a common multi-source spatial framework can distinguish different stages of internal economic-zone maturation and can support a more detailed understanding of where development is already concentrated and where comparatively large amounts of internal build-out remain to occur.

The remainder of the thesis is organized as follows. Chapter 2 reviews the relevant literature and establishes the Bangladesh economic-zone context. Chapter 3 presents the selected study area and the multi-source datasets, including their spatial and temporal

coverage. Chapter 4 describes the methods used for spatial boundary preparation, satellite-image acquisition and processing, image quality assurance, LULC model adaptation and classification, 100-m multi-source harmonization, quantitative extraction, and development-index formulation. Chapter 5 presents the experimental setup and the spatial and data-product validation of the processed datasets. Chapter 6 presents and discusses the LULC, nighttime-light, population, and development-index results for the twelve economic zones. Chapter 7 concludes the thesis, summarizes its contributions and limitations, discusses ethical, social, and environmental considerations, and outlines future research directions.

1.4 Research Questions

The study is guided by one primary research question and four supporting questions.

How have the 12 private economic zones influenced urbanization patterns within their footprints from 2018 to 2025?

1. How does the composition of farmland, water, forest, built-up, and meadow change within each economic zone between 2018 and 2025?
2. How do nighttime-light intensity and gridded population density change through time within the individual economic-zone boundaries?
3. Do the twelve economic zones exhibit distinct levels, rates, or temporal patterns of development rather than following a single common trajectory?
4. How can the observed internal development trajectories provide a spatial baseline for future assessment of potential urbanization and demographic spillover beyond the economic-zone boundaries?

The research questions are operationalized through annual LULC summaries, NTL and population density measures, three complementary indices, and cluster-level spatiotemporal comparisons. The fourth question is treated as a forward-looking spatial research direction; the empirical analysis in this thesis remains restricted to the zero-offset zone boundaries.

1.5 Scope and Delimitations

The geographical scope of the empirical analysis is restricted to twelve Private Economic Zones in Bangladesh that were fixed during the study design. Although the administrative registry of economic zones may change over time, the study population is intentionally held constant so that the longitudinal comparison is based on the same set of spatial units.

The temporal scope covers 2018–2025. The principal analytical variables are five LULC classes (built-up, farmland, water, forest, and meadow), nighttime lights, and gridded population. All principal zone-level results are calculated within the manually verified zero-offset economic-zone boundaries.

The study is an observational remote-sensing analysis. The constructed indices are indicators of spatial development intensity and are not direct measurements of industrial production, investment, employment, household income, or economic output. Consequently, relationships observed among LULC, NTL, and population should be interpreted as spatial associations and development signals rather than causal estimates of economic performance.

2. Literature Review and Bangladesh Economic Zone Context

2.1 Related Works

2.1.1 Remote Sensing of LULC and Urban Expansion

Land Use and Land Cover change has become a central framework for examining the spatial consequences of urbanization. Urban expansion is expressed not only through population growth but also through the conversion of agricultural land, vegetation, wetlands, water bodies, and other open surfaces into buildings, transport infrastructure, and impervious land. Global analyses have demonstrated that urban expansion can have substantial consequences for ecosystems, carbon stocks, biodiversity, and the spatial organization of human settlements [13]. For this reason, multi-temporal satellite imagery has become a major source of evidence for identifying where land conversion occurs, how rapidly it occurs, and which land-cover classes are most directly affected.

The general structure of a LULC change study consists of defining a spatial boundary and temporal series, acquiring comparable imagery, preparing the images for analysis, classifying land-cover classes, assessing classification quality, and comparing the derived maps through time. Depending on the application, supervised classification, machine-learning algorithms, and deep-learning semantic segmentation are widely used. The final outputs can be summarized through pixel counts, areal proportions, class transitions, change matrices, or other spatial indicators. In densely populated and heterogeneous urban environments, spatial resolution becomes especially important because individual buildings, roads, small ponds, tree canopies, and fragmented agricultural parcels can be smaller than the native pixel size of medium-resolution sensors.

2.1.2 LULC and Urbanization Studies in Bangladesh

Bangladesh provides an important setting for LULC research because demographic growth, industrial development, infrastructure expansion, and land conversion are occurring within a geographically constrained and densely settled landscape. Gazipur is a particularly relevant example because it has developed rapidly as an industrial hub adjacent to Dhaka. Arifeen et al. analyzed Gazipur from 1990 to 2020 using multi-temporal Landsat imagery and supervised classification and found strong urban expansion together with substantial changes in agricultural and other land-cover classes [1]. Uddin et al. subsequently analyzed Gazipur City Corporation from 2002 to 2022 and combined LULC classification with CA-ANN modelling to examine both historical change and future trajectories [2]. These studies show that remote sensing can provide a consistent basis for describing long-term urban transformation in Bangladesh.

A related case study in Bhaluka, Mymensingh, examined LULC change in a rapidly

industrializing area using Landsat 7 and Landsat 8 imagery and five land-cover classes. The study reported overall classification accuracies of 87.2% for 2002 and 89.6% for 2022, while the built-up class increased by 217.1% (6.56 km²) over the study period [14]. This result reinforces the broader Bangladesh evidence that industrialization can be accompanied by substantial conversion of previously non-built land into built-up surfaces, while also illustrating the continued use of medium-resolution Landsat imagery for long-term change detection.

The importance of high spatial resolution is further demonstrated by the BOLM study. BOLM provides pixel-level annotations for eleven LULC classes across approximately 4392 km² of the Dhaka metropolitan region and surrounding areas using high-resolution Bing imagery. Its benchmarking experiments demonstrated a clear trade-off between the fine spatial detail of high-resolution RGB imagery and the temporal and spectral advantages of Sentinel-2. The study also demonstrated the applicability of deep-learning segmentation models to heterogeneous urban and peri-urban landscapes in Bangladesh [3]. These findings are directly relevant to the present study because the target economic zones contain fragmented combinations of buildings, roads, water, vegetation, farmland, and open land that may be difficult to characterize reliably using a coarse spatial resolution alone.

2.1.3 Industrial Zones and Land Transformation in Bangladesh

The literature relating industrial development to spatial land transformation in Bangladesh provides an important bridge between general urbanization studies and the present economic-zone analysis. Simu et al. examined land-use change around the Dhaka Export Processing Zone using Landsat and GIS-based analysis, demonstrating that the major economic zone setting was associated with significant environmental and land-use pressures [10]. Basak et al. later examined urban dynamics around DEPZ within a 5 km surrounding radius and documented substantial development and population change in the zone’s surrounding catchment [9]. Their work is particularly important for the present study because it demonstrates that industrial development can be associated with regional spillover beyond the formal industrial boundary.

A more recent Gazipur-focused study further linked industrial and urban expansion with environmental change by examining LULC and land-surface temperature from 1995 to 2024. Using satellite imagery and machine-learning-based remote sensing in Google Earth Engine, the study reported a more than fourfold increase in built-up area and a long-term rise in land-surface temperature, with stronger thermal changes associated with industrialized areas [15]. Although land-surface temperature is not an input variable in the present thesis, this work is relevant because it demonstrates that the spatial consequences of industrial expansion extend beyond land-cover conversion alone and may also be reflected in environmental conditions.

More recent work has extended this type of analysis to economic-zone construction in environmentally sensitive coastal settings. Nabila and Tsuyuzaki examined land-use and land-cover changes from 1989 to 2021 in areas affected by economic-zone construction and found increases in built-up, bare, and artificial-water classes together with changes in forest cover [11]. Their subsequent before-after-control-impact analysis reported detectable vegetation changes associated with economic-zone construction and road development and showed that the effect could extend beyond the immediate site [12]. Together, these studies demonstrate that economic-zone construction can generate measurable spatial change and that the consequences may extend beyond the formal economic-zone boundary.

2.1.4 Nighttime Lights as a Complementary Urbanization Indicator

Nighttime Lights have been used extensively to delineate urban areas and to investigate socioeconomic and human-activity patterns from space. Early work demonstrated that satellite-observed city lights can provide useful information about urban extent and spatial development [16]. Later research showed that nighttime-light time series can be used to measure economic activity and long-term spatial change, while also emphasizing the importance of accounting for sensor and temporal characteristics [17]. A recent comparative study of Cape Town, Durban, and Johannesburg used VIIRS Day/Night Band observations to examine NTL trajectories from 2014 to 2023 and demonstrated that spatial NTL patterns can spread from city centres toward peripheral areas and correspond with developed urban land. The study also showed that NTL trajectories may be affected by contextual factors such as electricity-supply instability, highlighting the importance of interpreting nighttime-light changes within their socioeconomic and infrastructural context [18]. Recent syntheses have likewise expanded the use of nighttime-light remote sensing for urban applications and highlighted its value as a complementary source of information rather than a direct substitute for physical land-cover observations [6].

For the present study, NTL is useful because it represents a different dimension of development from LULC. Built-up land describes the physical surface, whereas nighttime illumination provides information associated with electricity use, infrastructure, roads, industrial activity, and human presence. The two signals may increase together during development, but they need not do so at exactly the same rate. A construction-dominated phase, for example, may produce rapid built-up expansion while nighttime-light intensity changes more gradually. Such differences are analytically informative when the objective is to understand development trajectories rather than to reduce development to a single physical land-cover class.

2.1.5 Gridded Population and Spatial Demographic Measurement

Population is a complementary dimension because urbanization involves both physical land conversion and changes in human concentration. Gridded population datasets transform administrative population information into spatially explicit surfaces that can be compared directly with remotely sensed variables. WorldPop uses dasymetric modelling and remotely sensed and ancillary information to disaggregate census population estimates into fine-resolution spatial grids [8, 19]. Such products are particularly useful for zone-level studies because they allow population intensity to be summarized inside an exact polygon rather than relying on an entire administrative unit.

Population should nevertheless be interpreted carefully in the context of industrial zones. A zone may experience substantial physical construction without an equivalent increase in resident population if workers commute from surrounding settlements. Conversely, a zone located in an already dense urban corridor may have a high population and NTL baseline before further industrial construction occurs. For this reason, the present study treats population as a complementary development indicator and combines it with LULC and NTL rather than using it as a stand-alone proxy for industrialization.

2.1.6 High-Resolution Imagery and Deep-Learning LULC Mapping

Deep-learning semantic segmentation has become an important approach for high-resolution LULC mapping because spatial context and fine feature boundaries can be learned directly from imagery. However, its success depends on the quality and spatial resolution of the training imagery. BOLD was specifically developed to address the scarcity of pixel-level high-resolution LULC annotations in Bangladesh and other developing-country settings. Its experiments showed that high-resolution Bing imagery consistently provided stronger fine-scale segmentation performance than the tested Sentinel-2 inputs, although the authors also emphasized the value of Sentinel-2’s multispectral and temporal information [3].

This spatial-temporal trade-off is central to the present work. Bing imagery provided an important basis for the previously developed high-resolution LULC framework, but the imagery cannot be relied upon as a consistently updated annual source for the entire 2018 to 2025 period. Sentinel-2 provides repeated observations but has a native 10 m spatial resolution. The present study therefore uses Sentinel-2 observations together with the Gamma Earth S2DR4 super-resolution framework to create a finer-resolution RGB product for annual LULC inference [5]. The resulting workflow is intended to combine the temporal availability of an open satellite programme with the spatial requirements of detailed zone-level classification.

2.2 Research Gap and Positioning

The literature demonstrates that the individual components of the present framework are well established. Remote sensing is widely used to measure LULC change; Bangladesh studies have documented rapid urban expansion and associated landscape transformation; industrial-zone studies demonstrate that economic-zone development can generate detectable land-use and ecological changes; nighttime lights provide a complementary signal of human activity and illumination; and fine-resolution deep-learning approaches improve the representation of heterogeneous urban land cover.

The Bangladesh evidence is particularly relevant but remains spatially fragmented. Studies of Gazipur, Bhaluka, and the Dhaka Export Processing Zone demonstrate strong industrially associated LULC and urban changes, while recent work has additionally linked industrial expansion with thermal environmental effects [1, 2, 9, 14, 15]. At the same time, VIIRS-based NTL research demonstrates the value of temporally consistent illumination measurements for identifying urban-development trajectories and spatial expansion [18].

The remaining gap is therefore primarily one of analytical integration, spatial consistency, and study-unit definition. Existing Bangladesh studies have generally focused on cities, districts, individual industrial developments, ecological regions, or surrounding catchments. Even the economically focused industrial-zone studies do not establish a common annual framework for comparing the internal development trajectories of twelve separate Private Economic Zones using the same zero-offset spatial boundary and the same combination of LULC, NTL, and population indicators [9, 11, 12]. The present study addresses this gap by using the same exact economic-zone boundary for all years and by integrating LULC, NTL, and population indicators within that fixed boundary.

The present study addresses this gap by using the same exact economic-zone boundary for all years and by integrating LULC, NTL, and population indicators within that fixed boundary. The principal empirical unit is the zero-offset economic-zone footprint. The wider buffer framework is retained as a spatial foundation for future spillover analysis, but

the current analysis focuses specifically on the question of how much and how rapidly the interior of each economic zone has changed.

2.3 Economic Zones and the Bangladesh Context

2.3.1 Institutional Development of Economic Zones

Bangladesh’s institutional framework for planned industrial development evolved from the earlier Export Processing Zone system toward a broader economic-zone model. The Bangladesh Economic Zones Act, 2010 established the Bangladesh Economic Zones Authority (BEZA) and provided a national framework for developing different categories of economic zones. Private Economic Zones are particularly relevant to this research because private developers are responsible for land acquisition or leasing, infrastructure provision, and industrial development while operating under BEZA’s regulatory framework [20–22]. The twelve zones analyzed in the present study were fixed as the study population based on the project dataset and the BEZA private-zone framework used during study design.

Table 1: Types of Economic Zones in Bangladesh within the BEZA framework.

Type	Who develops it	Key characteristics
Government EZ	Government of Bangladesh	Developed on state land using public resources and administered through the government framework.
Private EZ	Private individual, group, company, or consortium	The private developer acquires or leases land, develops infrastructure, and provides serviced industrial plots under the BEZA regulatory framework.
PPP EZ	Government and private-sector partner	Development responsibilities, financing, risks, and management are shared through a formal public-private partnership arrangement.
G2G EZ	Government of Bangladesh and a foreign government	Developed through bilateral government-to-government arrangements involving agreed land, financing, and investment frameworks.
Special / Specialized EZ	Government, private sector, or PPP depending on the project	Established for a defined industrial, strategic, or sector-specific purpose rather than general manufacturing alone.
Tourism EZ	Government or PPP partners	Sector-specific development intended primarily for tourism, hospitality, and related investment activities.

Private Economic Zones differ from government, public-private partnership, government-to-government, and specialized economic zones in ownership, financing, development responsibilities, and management arrangements. In private zones, the developer has a direct role in land preparation and infrastructure development. Consequently, the physical condition of the land inside the zone provides a meaningful spatial record of implementation progress. At the same time, approval or licensing alone does not imply that a zone has achieved substantial physical build-out. The distinction between formal

approval and observed land transformation is therefore an important motivation for a remote-sensing-based assessment.

The twelve Private Economic Zones included in this study are geographically heterogeneous. Several are located in the Dhaka-Narayanganj-Munshiganj industrial corridor, while others occur in Gazipur, Sirajganj, Chattogram, Kishoreganj, and Cumilla. This geographical diversity is useful for comparison because the zones differ in surrounding population density, existing urbanization, transportation accessibility, river or coastal setting, and apparent stage of industrial development.

The working spatial database used in this research records each zone as an individual polygon together with its district, Upazila, licensing information, and approximate area information. The location and developer fields are separated in the following tables so that administrative geography and development responsibility remain distinct.

2.3.2 Spatial Extent and Land Status of the Selected Private Economic Zones

The physical extent of an economic zone can be reported in several ways, including the area formally licensed or allotted under the BEZA framework, land acquired or controlled by the developer, and the larger project area planned for subsequent expansion. These measures should not be treated as interchangeable. For example, the Karnaphuli Dry Dock Special Economic Zone occupies about 45 acres in total, of which 20.98 acres were allotted by BEZA and the remainder was developer-owned land [23]. Similarly, the Cumilla Economic Zone has a 246.36-acre licensed area, while its broader project footprint is reported at approximately 361 acres [24, 25]. Table 2 therefore distinguishes the licensed, acquired, or allotted area from the broader planned or project area wherever the available documentation supports the distinction.

The approximate areas in Table 2 are contextual descriptors rather than substitutes for the analytical polygons. In the present study, all LULC, nighttime-light, population, and composite-index calculations are based on the digitized zero-offset boundary of each economic zone. This distinction is important because a developer’s larger project footprint may include land intended for future expansion, whereas the empirical analysis requires a fixed spatial unit whose boundary remains constant over the study period.

2.3.3 Development and Operational Chronology of the Selected Private Economic Zones

The chronology of a private economic zone requires careful separation of several institutional and physical milestones. Government declaration establishes the zone within the national economic-zone framework, while a pre-qualification licence permits progression toward development and a final BEZA licence provides formal regulatory authorization for establishment, development, operation, and related activities. These administrative events do not necessarily occur in the same year as land development or industrial production. In particular, physical development may begin before final licensing, while commercial production may commence years after a zone has been formally licensed. The chronology in Table 3 therefore treats these milestones separately rather than assigning a single year to the concept of “establishment” [21, 26].

Table 2: Spatial extent and land status of the twelve selected Private Economic Zones.

No.	Economic Zone	Location / Upazila	Developer	Licensed, Acquired, or Allotted Area (acres)	Broader Planned / Project Area (acres)
1	Meghna Economic Zone	Sonargaon, Narayan-ganj	Meghna Group of Industries	≈67.92 licensed	245
2	Abdul Monem Economic Zone	Gazaria, Munshiganj	Abdul Monem Limited	189.94 licensed	216 owned; expandable beyond 300
3	Aman Economic Zone	Sonargaon, Narayan-ganj	Aman Group	≈83.14 approved/licensed	150
4	Bay Economic Zone	Gazipur	Bay Group	≈37.59 licensed/approved	–
5	Meghna Industrial Economic Zone	Sonargaon, Narayan-ganj	Meghna Group of Industries	≈71.90 licensed	156
6	City Economic Zone	Rupganj, Narayan-ganj	City Group	77.96 licensed / established	77.96
7	Sirajganj Economic Zone	Sirajganj Sadar area	Sirajganj Economic Zone consortium	≈1,041 reported zone area	–
8	Karnaphuli Dry Dock Special EZ	Anwara, Chattogram	Karnaphuli Dry Dock Limited	20.98 allotted by BEZA	≈45
9	East West Special Economic Zone	Keraniganj, Dhaka	East West Property Development consortium	≈102.69 first phase	≈218
10	Kishoreganj Economic Zone	Pakundia, Kishoreganj	Nitol Niloy Group	91.63 established area	–
11	Hoshendi Economic Zone	Gajaria, Munshiganj	City Group	≈108 established/licensed	108
12	Cumilla Economic Zone	Meghna, Cumilla	Meghna Group of Industries	246.36 licensed	≈361

Note: The terminology “licensed,” “acquired,” “allotted,” and “established” follows the wording of the cited source and should not be interpreted as legally equivalent categories. Broader project areas refer to developer-controlled, planned, or subsequently expanded footprints rather than the fixed analytical boundary used in this study. Approximate values are rounded where the source reports an approximate area [23–36].

Table 3: Development and operational chronology of the twelve selected Private Economic Zones.

No.	Economic Zone	Establishment or Declaration Year	BEZA Final Licence Year	Physical Development Start	Operational / Commercial Year
1	Meghna Economic Zone	2016	2016	2016	2018
2	Abdul Monem Economic Zone	2016	2017	2016	2018
3	Aman Economic Zone	2017	2017	2016	2017
4	Bay Economic Zone	2017	2017	2016	2018 ¹
5	Meghna Industrial Economic Zone	2017	2017	2016	2018
6	City Economic Zone	2017	2018	by 2018	2018/2019 ²
7	Sirajganj Economic Zone	2018	2018	2019	Not confirmed
8	Karnaphuli Dry Dock Special EZ	2019	2019	by 2019	Not confirmed ³
9	East West Special Economic Zone	2019	2019	by 2019	Not confirmed
10	Kishoreganj Economic Zone	2019	2019	by 2019	2022 ⁴
11	Hoshendi Economic Zone	2019	2020	2020 onward	2022 ⁵
12	Cumilla Economic Zone	2022	2022	before/by 2022	Not confirmed

Notes: “Not confirmed” is used where the available evidence does not establish a reliable year of full commercial operation. ¹ 2018 denotes the first documented operating industrial unit in the Bay Economic Zone rather than full build-out of the entire zone. ² City Group reports operations beginning in 2018, while formal inauguration and independent commercial documentation fall in 2019. ³ 2024 was a planned start date for the dry dock and container-port facilities, not a verified full operational date. ⁴ 2022 denotes a launch milestone for Kishoreganj; it is not treated here as evidence of sustained commercial production. ⁵ 2022 denotes the inauguration and developer-reported start of zone operations at Hoshendi; full commercial production is treated separately in the accompanying discussion.

The first group of private zones illustrates an early transition from formal declaration to visible industrial development. Development activities at Meghna Economic Zone, Abdul Monem Economic Zone, Aman Economic Zone, Bay Economic Zone, and Meghna Industrial Economic Zone were formally initiated in February 2016, before several of these zones received their final BEZA licences [37]. Meghna subsequently received the country’s first final private economic-zone licence in August 2016, and industrial units in the Meghna and Meghna Industrial zones were inaugurated in 2018 [38, 39]. Abdul Monem received its final licence in January 2017, while Honda’s manufacturing facility in the zone began production in 2018 [40, 41]. Aman received its final licence in 2017, and Aman Cement’s industrial operation in the zone is documented from 2017 [42, 43]. Bay received final approval in April 2017; the developer and contemporary reporting document industrial units operating subsequently, with production activity reported from 2018 [44, 45]. These cases show that declaration or licensing years and observable industrial activity can differ by one or more years.

City Economic Zone was formally declared in 2017 and received its final BEZA licence

in January 2018. At the time of licensing, machinery for industrial units had already been procured and electricity connections were in place, indicating that physical preparation had progressed before final licensing [46]. City Group reports that the zone started operations in 2018, while the formal inauguration took place in April 2019 and legal documentation records commercial activity by 2019 [47, 48]. Sirajganj Economic Zone received final approval in 2018 and reached a substantial stage of land development during the following years. Contemporary reporting recorded roughly 60% of land-development work completed in 2022, while a 2024 site assessment reported ongoing earthwork and an expectation of entering production in the following year [49, 50]. Accordingly, 2019 is used as the physical-development start in Table 3, but a confirmed commercial-operation year is not assigned.

The later zones further demonstrate why physical development and commercial operation should not be inferred from licensing alone. Karnaphuli Dry Dock Special Economic Zone received its final licence in 2019; road and power works had been completed and jetty construction was underway at that time. Subsequent reporting stated that the 100,000-DWT dry dock and associated container port were expected to begin operation in 2024, but this was a planned milestone rather than independent confirmation that the full facilities became operational [23, 51]. East West Special Economic Zone received final licensing in 2019, with its first development phase covering roughly 102.69 acres within a larger project area of about 218 acres; however, the sources reviewed do not provide sufficiently firm evidence for assigning a commercial-operation year [34, 52]. Kishoreganj Economic Zone received its final licence in February 2019 on 91.63 acres. The zone was subsequently launched, but later reporting indicates that industrial activity was constrained by utility shortages; accordingly, 2022 is treated only as a launch milestone rather than evidence of sustained commercial operation [53, 54]. Hoshendi Economic Zone was formally declared in 2019 and received its final BEZA licence in January 2020 on approximately 108 acres. City Group records an inauguration on 20 November 2022, but the available legal and development documentation distinguishes inauguration from full commercial production [55–57]. Finally, Cumilla Economic Zone received its final BEZA licence on 10 April 2022 for 246.36 acres; subsequent land acquisition expanded the broader project footprint to approximately 360–361 acres, while reporting continued to describe industrial development and production as a subsequent stage [24, 25, 58].

This chronology is directly relevant to the present remote-sensing framework. The empirical analysis measures observable land-cover and development signals within fixed economic-zone boundaries from 2018 to 2025; therefore, a licence year should not be interpreted as the beginning of physical urbanization, and a planned operation date should not be treated as confirmed industrial activity. Instead, the chronology provides institutional context against which changes in built-up land, nighttime illumination, population density, and the derived composite indices can be interpreted. This distinction is particularly important for zones that remained in land-development or construction stages for several years after licensing.

The wider spatial framework includes concentric buffers around the individual economic zones for potential future analysis of development spillover. However, the present thesis keeps the empirical results restricted to the exact zero-offset boundary of each zone, ensuring that the observed annual trajectory is associated with a fixed physical spatial unit rather than changes in the analytical boundary.

3. Study Area and Data

3.1 Motivation and Purpose

The primary motivation for this study arises from the need to distinguish between the formal establishment of a Private Economic Zone (PEZ) and its observable physical development. Governmental approval, licensing, land allocation, or planned investment does not necessarily imply that substantial industrial infrastructure has already been constructed within the designated area. A spatially explicit, remotely sensed record therefore provides an independent basis for examining how the physical character of a zone changes through time.

A second motivation is the need for a consistent basis for comparison among multiple Private Economic Zones. The selected zones differ in physical extent, geographic setting, surrounding urbanization, accessibility, and apparent stage of development. Direct comparison becomes difficult when different spatial definitions, spatial resolutions, or observation periods are used. The present study therefore applies a common zero-offset analytical boundary to all twelve selected zones and follows a common annual observation framework from 2018 to 2025.

A third motivation is that physical land conversion alone does not fully represent the development environment associated with an economic zone. Built-up land describes the physical transformation of the surface, while nighttime lights provide a complementary signal associated with artificial illumination and human activity, and gridded population represents the demographic dimension. The combined use of these datasets provides a broader spatial basis for evaluating development intensity than any single variable considered alone.

Finally, the study establishes a reproducible spatial and data-processing baseline for future monitoring. The empirical analysis reported in this thesis is intentionally restricted to the exact, zero-offset footprints of the twelve economic zones. The surrounding multi-scalar buffers, intersecting Upazila units, and Upazila Group (UG) Zones were nevertheless created and retained as a reusable spatial framework for future regional and spillover studies. This avoids repeating the same spatial preparation, satellite-data acquisition, and preprocessing effort in subsequent work.

3.2 Study Area and Selected Private Economic Zones

The study area comprises twelve Private Economic Zones in Bangladesh selected from the PEZ framework used during the design and inception phase of the research. The spatial and temporal analysis was fixed to these twelve zones so that the same study population could be observed consistently across all years from 2018 to 2025. Although the administrative listing of private economic zones may change over time, no additional zones were introduced into the present longitudinal analysis.

Figure 1 provides the national spatial distribution and individual spatial footprints of the twelve zones. The zero-offset polygons shown in the figure represent the exact analytical units used for the reported longitudinal results. The map is therefore both a geographic overview and a visual definition of the primary empirical study units.

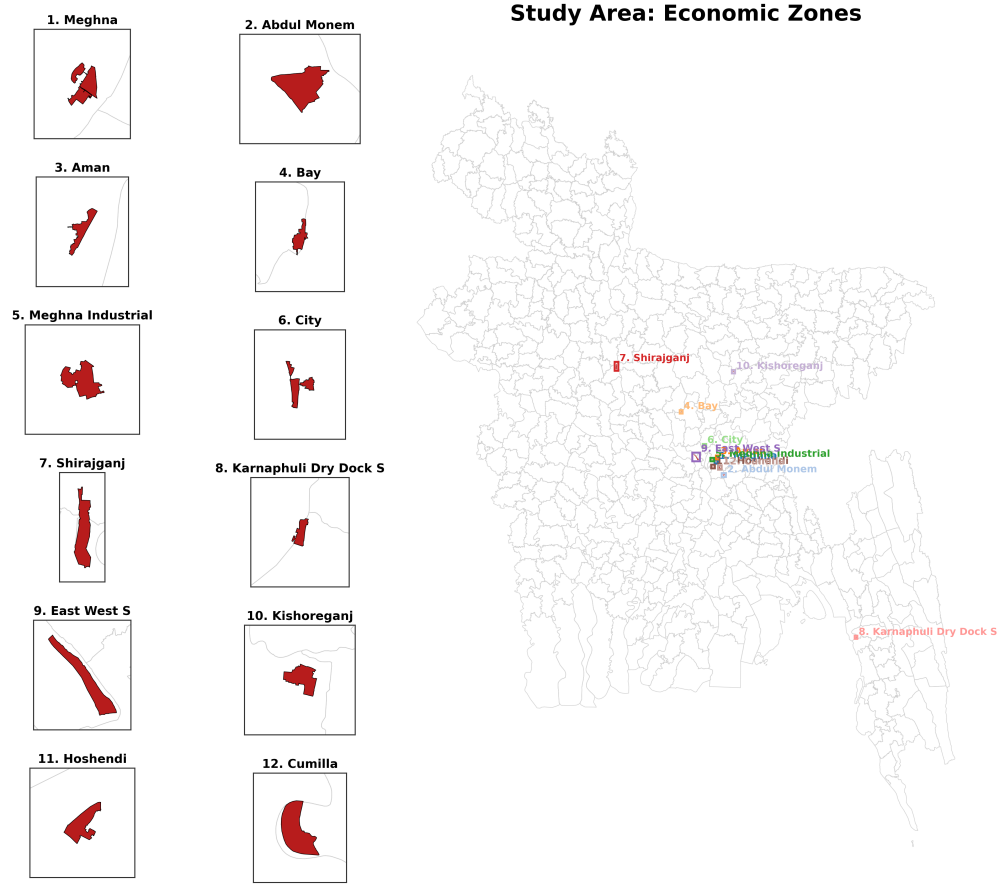


Figure 1: Spatial distribution of the twelve Private Economic Zones selected as the primary study areas. The inset panels show the individual zero-offset economic-zone polygons, while the Bangladesh map provides their national spatial context.

The twelve economic zones are geographically heterogeneous. Several are concentrated in the Dhaka–Narayanganj–Munshiganj industrial corridor, while others are located in Gazipur, Sirajganj, Chattogram, Kishoreganj, and Cumilla. Their surrounding environments consequently differ in terms of existing built-up development, agricultural land, water bodies, vegetation, transportation connectivity, and population concentration. This heterogeneity is important because it allows the longitudinal analysis to distinguish zones that follow different stages or pathways of development.

Official BEZA information and available zone-specific materials were used as reference sources for identifying the selected zones. The detailed geometric delineation of the analytical boundaries is described in Chapter 4; the present chapter focuses on the resulting study units and their data context.

3.2.1 Spatial Distribution and Characteristics of the Twelve Zones

Table 4 summarizes the twelve selected zones using the administrative and project level information retained in the working study. After studying these economic zones, we created polygon shape maps using QGIS and Google Earth software and listed their measured areas in acres in this table.

Table 4: Spatial and administrative details of the selected twelve Private Economic Zones.

No.	Economic Zone Name	Upazila	Studied Area (Acres)	Coordinates (Lat, Long)
1	Sirajganj Economic Zone	Sirajganj Sadar	1041.43	24.3912° N, 89.7543° E
2	Abdul Monem Economic Zone	Gazaria, Munshiganj	216.00	23.5422° N, 90.6121° E
3	Aman Economic Zone	Sonargaon, Narayanganj	150.00	23.6210° N, 90.5982° E
4	Bay Economic Zone	Gazipur Sadar	65.00	24.0125° N, 90.4123° E
5	City Economic Zone	Rupganj, Narayanganj	77.96	23.7845° N, 90.5214° E
6	Meghna Economic Zone	Sonargaon, Narayanganj	245.00	23.6123° N, 90.6012° E
7	Meghna Industrial Economic Zone	Sonargaon, Narayanganj	110.00	23.6155° N, 90.6055° E
8	Karnaphuli Dry Dock Special EZ	Anwara, Chattogram	100.00	22.2541° N, 91.8214° E
9	East West Special Economic Zone	Gazipur Sadar	100.00	23.9512° N, 90.4011° E
10	Kishoreganj Economic Zone	Pakundia, Kishoreganj	91.63	24.3312° N, 90.6621° E
11	Cumilla Economic Zone	Meghna, Cumilla	250.00	23.6012° N, 90.7214° E
12	Hoshendi Economic Zone	Gazaria, Munshiganj	108.00	23.5512° N, 90.6214° E

3.3 Multi-Tiered Spatial Study Framework

Although the primary empirical study units are the twelve zero-offset economic-zone footprints, the project established a broader spatial framework around those units. This framework was created before large-scale data acquisition so that imagery and derived datasets could be prepared once for the complete relevant spatial extent and subsequently reused for future regional analysis.

The spatial framework consists of four related levels.

3.3.1 Zero-Offset Economic-Zone Boundaries

The zero-offset boundary represents the exact spatial footprint of each selected Private Economic Zone without an additional external buffer. These twelve polygons are the principal analytical units of this thesis. The annual LULC, NTL, population, and composite-index results presented in Chapters 5 and 6 are calculated within these exact zone boundaries.

3.3.2 Buffer Zones

Concentric buffer extents were also established around each zero-offset economic-zone boundary at 1 km, 2 km, 3 km, 4 km, and 5 km. The 5-km extent was retained as the

principal surrounding buffer because it provides a consistent regional envelope around the economic-zone footprints.

These buffer zones are not treated as the primary empirical units of the present thesis. Rather, they were prepared as a reusable spatial framework for future investigation of surrounding urbanization and possible spillover effects. The same prepared spatial extents also support visual validation of how the workflow could be applied beyond the zero-offset boundary.

3.3.3 Intersecting Upazila Administrative Units

Because economic-zone boundaries and their surrounding buffers can cross administrative boundaries, the relevant Bangladesh Upazila polygons were identified using the administrative boundary dataset used in the project. These Upazila geometries provide an administrative reference layer for future analysis of the broader areas surrounding the economic zones.

3.3.4 Upazila Group (UG) Zones

Several economic zones are geographically close to one another, especially in the Dhaka–Narayanganj–Munshiganj area. Their 5-km buffers can therefore overlap. The project retained the dissolved buffer geometries and grouped the relevant Upazilas into five spatially separated Upazila Group (UG) Zones. These UG Zones function as large spatial supersets that contain the relevant economic zones, buffer extents, and intersecting Upazila areas.

The UG Zones were prepared primarily to make high-volume satellite-data acquisition and subsequent processing more efficient. Instead of repeatedly downloading overlapping areas for individual zones, a single UG Zone could provide the common source coverage for all contained study units. The resulting UG Zones and their underlying Upazila geometries were also retained for future regional analysis. They are not used as the primary spatial units for the results reported in this thesis.

Table 5: Summary of the five Upazila Group (UG) Zones prepared as reusable spatial supersets.

UG Zone	Total Upazilas	Economic Zones contained within the UG spatial framework	Reference coordinate
UG1	33	Meghna Economic Zone; Meghna Industrial Economic Zone; Abdul Monem Economic Zone; Aman Economic Zone; Bay Economic Zone; City Economic Zone; Hoshendi Economic Zone	23.6181, 90.5817
UG2	10	Kishoreganj Economic Zone	24.0419, 90.3259
UG3	19	Sirajganj Economic Zone	24.3827, 89.8006
UG4	12	Karnaphuli Dry Dock Special Economic Zone; East West Special Economic Zone	22.2852, 91.8969
UG5	14	Cumilla Economic Zone	24.3441, 90.7698

3.4 Multi-Source Dataset Framework

The longitudinal analysis was designed around three principal analytical data streams: high-resolution optical satellite imagery for physical land-cover characterization, nighttime-light radiance for spatially distributed artificial illumination, and gridded population

data for the demographic dimension. A fourth data source, the Bangladesh Open LULC Map (BOLM) framework, supplied the high-resolution reference and training information required for adapting the LULC classification workflow.

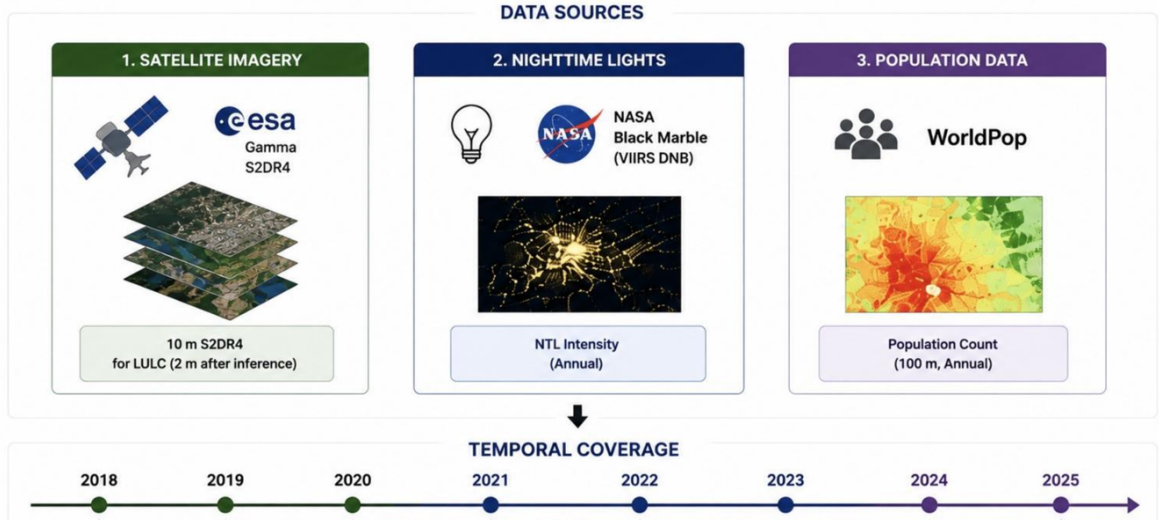


Figure 2: Multi-source data framework and temporal coverage used in the study. Sentinel-2 imagery is transformed through the Gamma S2DR4 workflow to provide a 2-m analytical optical product for LULC inference; VIIRS VNP46A3 provides nighttime-light radiance observations; and WorldPop provides 100-m gridded population estimates over the 2018–2025 study period.

Table 6 summarizes the principal datasets used in the longitudinal spatial analysis.

Table 6: Principal datasets used in the longitudinal spatial analysis.

Data category	Dataset / source	Native spatial resolution	Temporal coverage / representation
Optical satellite imagery	Copernicus Sentinel-2 Level-2A with Gamma S2DR4 super-resolution processing [4, 5]	10 m input; 2 m analytical output	Annual optical observations organized for 2018–2025
Nighttime lights	VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Monthly L3 Global 15 arc-second Linear Lat/Lon Grid V2 (VNP46A3) [6]	~15 arcsec (~462 m)	Monthly source product; annual observations prepared for 2018–2025
Population	WorldPop Bangladesh population grid [8]	100 m	Annual gridded population estimates, 2018–2025
LULC Model Adaptation	Bangladesh Open LULC Map (BOLM) high-resolution model adaptation framework [3]	Adjusted and preprocessed to 2m in the training	LULC model adaptation and preprocessed for the training for Gamma Sat Images

The three analytical data streams were organized on a common annual framework

from 2018 to 2025. Their native spatial resolutions differ substantially; therefore, the datasets were subsequently harmonized to a common 100-m spatial framework during the methodological processing stage. The BOLM data are treated as reference/training material rather than as a direct annual analytical dataset.

Under the current thesis-wide continuous table numbering, this table is intended to appear as **Table 6**. The final number should be allowed to update automatically after the earlier tables are fixed. The table is intentionally limited to source, resolution, and temporal information; the role of each dataset is described in the surrounding text rather than repeated as a separate column.

3.5 Types and Sources of Data

3.5.1 High-Resolution Optical Satellite Imagery (Sentinel-2 and Gamma S2DR4)

The optical data framework is based on Copernicus Sentinel-2 Level-2A imagery and the Gamma S2DR4 super-resolution workflow. Sentinel-2 provides repeated multispectral observations at a native 10-m spatial resolution, supplying the temporal continuity required for the 2018–2025 longitudinal analysis. The Gamma S2DR4 model was adopted to transform the optical observations into a synthesized 2-m RGB analytical product suitable for the high-resolution LULC workflow [4, 5].

During the initial data-acquisition stage, alternative high-resolution imagery sources were considered. Commercial imagery such as PlanetScope provides finer native spatial resolution, but the available institutional access and download limitations were not suitable for repeated coverage of the complete spatial extent required by this project. The final data framework therefore used Sentinel-2 as the recurring optical source and Gamma S2DR4 as the super-resolution component. Figure 3 illustrates the downloaded and converted 2m Gamma S2DR4 satellite imagery 4 km x 4 km tiles.



Figure 3: Representative Gamma S2DR4 2-m satellite tiles obtained after Sentinel-2 processing and super-resolution conversion. The example illustrates the high-resolution optical inputs assembled for subsequent mosaicking and LULC inference.

3.5.2 Nighttime-Lights Radiance Data (VIIRS VNP46A3)

Nighttime lights provide a complementary spatial signal associated with artificial illumination, infrastructure, and human activity. The study uses the VIIRS/NPP Lunar BRDF-Adjusted Nighttime Lights Monthly L3 Global 15 arc-second Linear Lat/Lon Grid Version 2 product, VNP46A3 [6]. The product has a native spatial resolution of approximately 15 arc-seconds, corresponding to roughly 462 m near the equator.

The VNP46A3 product contains continuous radiance measurements rather than categorical land-cover classes. The source observations were therefore retained as numerical radiance data and subsequently transformed to the common 100-m framework during the methodological processing stage.

Bangladesh Nighttime Lights (NTL) Radiance — 2025

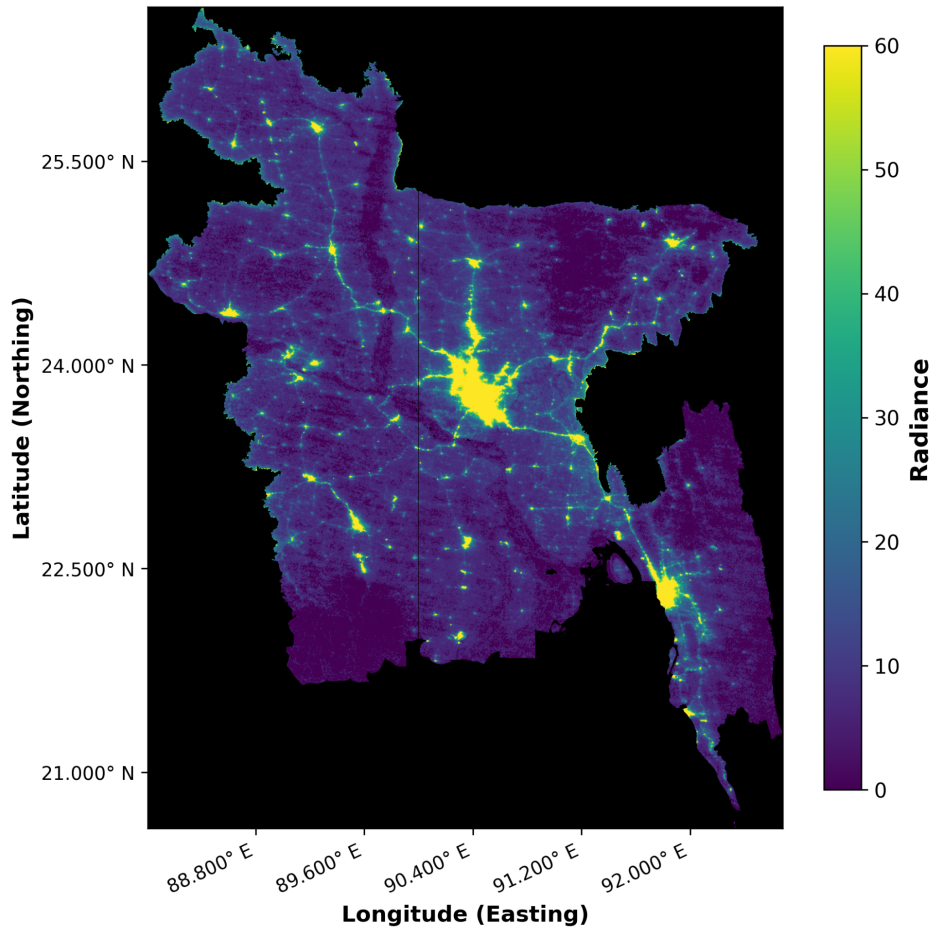


Figure 4: Bangladesh-wide VIIRS nighttime-light radiance visualization for 2025, shown as an example of the national NTL data used before extraction to the exact economic-zone boundaries.

Figure 4 illustrates the national spatial distribution of the 2025 NTL observations. The figure documents the source-data product visually, while the numerical extraction and 100-m alignment procedures are described in Chapter 4.

3.5.3 High-Resolution Population Density Grids (WorldPop)

The demographic component is represented by the WorldPop population grid for Bangladesh at approximately 100-m spatial resolution [8]. The raster values represent estimated population counts per grid cell. The use of a spatially gridded demographic

dataset allows population intensity to be summarized within the exact economic-zone footprints rather than relying only on broad administrative totals.

The native 100-m spatial resolution of the WorldPop layer is compatible with the common 100-m analytical framework adopted in the study. The population values are retained as numerical observations and are subsequently processed and extracted using the procedures described in Chapter 4.

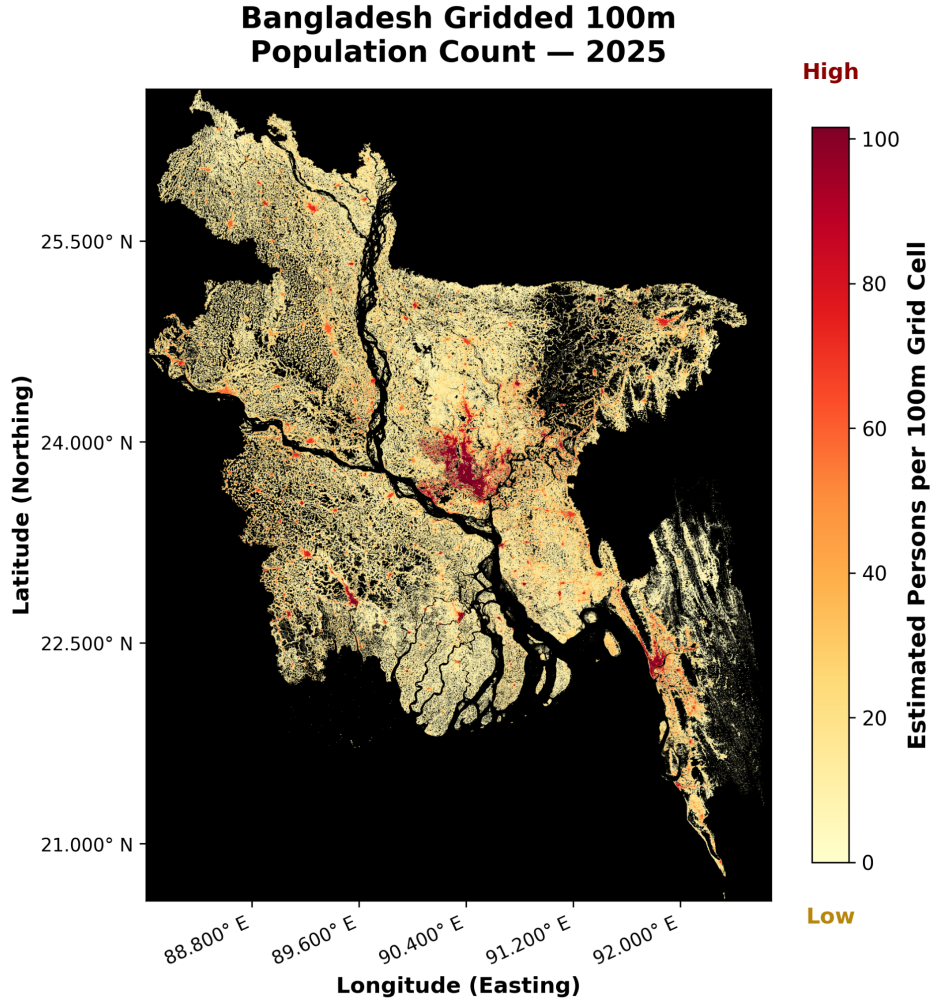


Figure 5: Bangladesh-wide WorldPop population grid visualization for 2025, illustrating the spatial distribution of estimated population counts in the source demographic dataset.

Figure 5 shows the national spatial pattern of the 2025 population surface. The figure is included as a representative data-product example; the actual longitudinal extraction performed for this thesis uses the exact zero-offset boundaries of the twelve economic zones.

3.5.4 Land Use Land Cover (LULC) Reference

The LULC classification component is based on adaptation the Bangladesh Open LULC Map (BOLM) high-resolution classification framework [3]. BOLM provides the reference class structure and high-resolution labeled information used as the starting point for adapting the LULC workflow to the Gamma S2DR4 2-m imagery.

The present study therefore distinguishes between two roles of LULC-related data. The BOLM-derived labeled material is used as the reference and training source for model adaptation, while the annual 2-m LULC inference generated from the adapted

workflow constitutes the analytical land-cover dataset used for the longitudinal results. Figure 6 presents a representative visualization of the inferred LULC product for the East West Special Economic Zone in 2018, shown within an extended 5-km contextual buffer. The figure illustrates the spatial distribution of the five analytical LULC classes in the inferred raster product and provides a visual example of the land-cover information used in the subsequent spatial analysis. Detailed preprocessing, semantic class aggregation, training-data preparation, and model adaptation are described in Chapter 4.

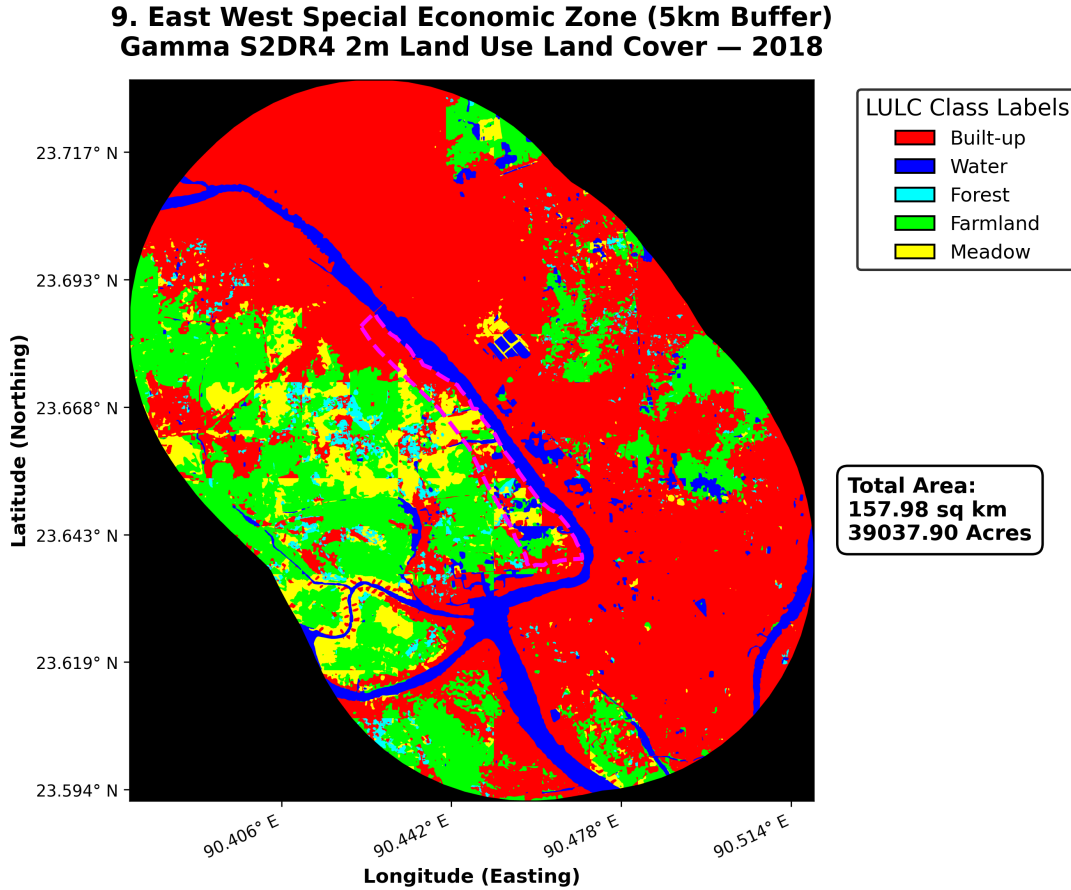


Figure 6: Representative 2-m LULC inference for the **East West Special Economic Zone, 2018**, within the extended 5-km contextual buffer. The figure illustrates the spatial distribution of the five analytical LULC classes derived from the adapted classification workflow.

3.6 Temporal Coverage

The primary temporal coverage of the study spans eight consecutive years, from 2018 through 2025. This period provides a common longitudinal window over which the twelve economic zones can be compared using the same spatial definitions.

The optical imagery, LULC inference, nighttime-light observations, and population layers are organized on an annual basis for the longitudinal analysis. The resulting annual records allow the study to examine both gradual and non-linear changes rather than relying only on two endpoint observations.

A special consideration applies to the earliest optical baseline. Because the Sentinel-2 Level-2A archive was not uniformly available at the beginning of the study period, the acquisition workflow used the nearest acceptable observations available under the project’s temporal fallback rules when necessary to construct the 2018 spatial baseline. The detailed fallback and quality-control procedure is documented in Chapter 4.

Temporal coverage summary: The principal longitudinal datasets are organized over the common study period 2018–2025 (eight annual observations).

3.7 Data Acquisition and Preparation Overview

The overall acquisition strategy used the prepared spatial framework to obtain source data for the complete geographic extent required by the project. The five Upazila Group (UG) Zones were used as acquisition supersets so that overlapping economic-zone and buffer areas did not have to be downloaded repeatedly.

For the optical data, the source Sentinel-2 imagery was acquired and transformed through the Gamma S2DR4 workflow to generate the high-resolution 2-m analytical product. The NTL data were obtained from the NASA Earthdata VIIRS VNP46A3 product and prepared as geospatial radiance rasters, while the WorldPop population surfaces were obtained as 100-m gridded population estimates. The BOLM framework provided the reference information required for the LULC model adaptation.

The detailed procedures used to acquire, filter, process, validate, reproject, mosaic, and align these datasets are intentionally separated from this descriptive chapter and are presented in Chapter 4. In this way, Chapter 3 documents *what data were used and where they came from*, while Chapter 4 documents *how the data were processed and analyzed*.

The present results use only the exact zero-offset boundaries of the twelve Private Economic Zones. The prepared 1–5 km buffers, intersecting Upazila boundaries, and Upazila Group (UG) Zones are retained as a reusable spatial and data-acquisition framework for future studies of surrounding urbanization and spillover. Their preparation is therefore part of the research infrastructure, but not part of the primary result domain of this thesis.

4. Methods and Materials

4.1 Methodological Framework

The methodological framework was organized as a sequential, multi-stage geospatial analysis designed to integrate spatial boundaries, multi-sensor observations, deep-learning-based LULC inference, a common 100-m spatial framework, quantitative metric formulation, and spatiotemporal assessment. The six principal methodological stages are summarized in Figure 7. The complete computational workflow, including the detailed processing and quality-control operations, is presented in Figure 8.

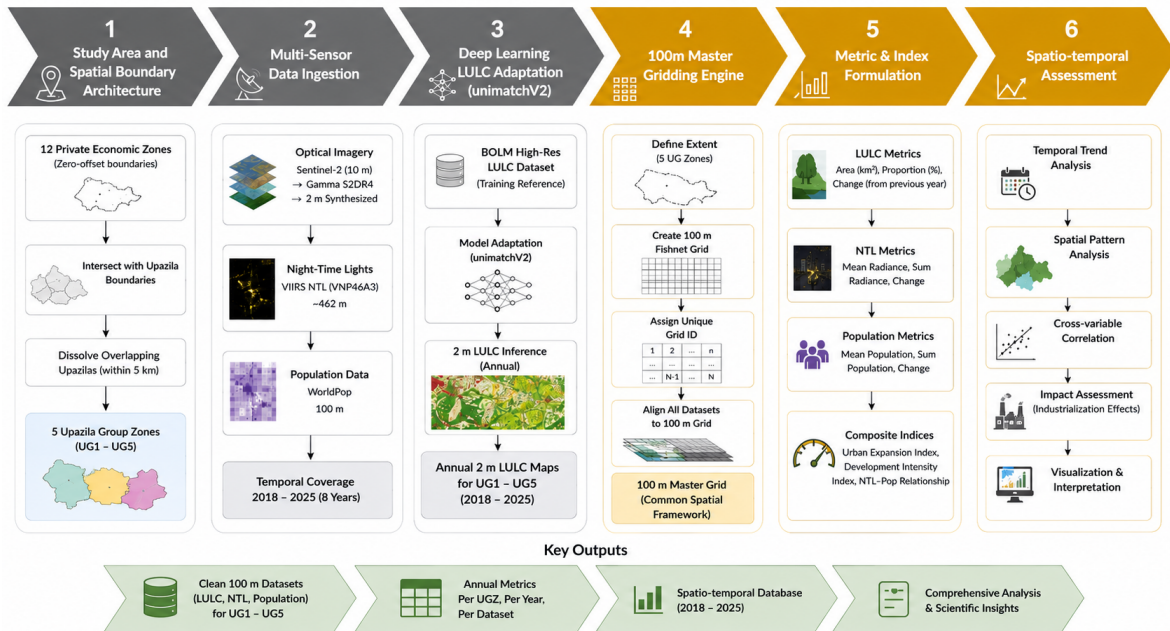


Figure 7: High-level methodological stages adopted for the study, from study-area definition and multi-sensor data ingestion to 100-m gridding, metric formulation, and spatiotemporal assessment.

Figure 7 provides a high-level representation of the methodological stages and their overall progression, while Figure 8 expands these stages into the detailed computational workflow. The detailed flow shows how the study-area boundaries and buffered UGZ framework are established, multi-source datasets are acquired and processed, the LULC model is adapted and applied, and the resulting datasets are aligned to a common 100-m spatial framework. It further illustrates the subsequent masking, automated batch processing, metric extraction, and spatiotemporal analysis used to generate the final analytical outputs.

Methodology Flow Diagram

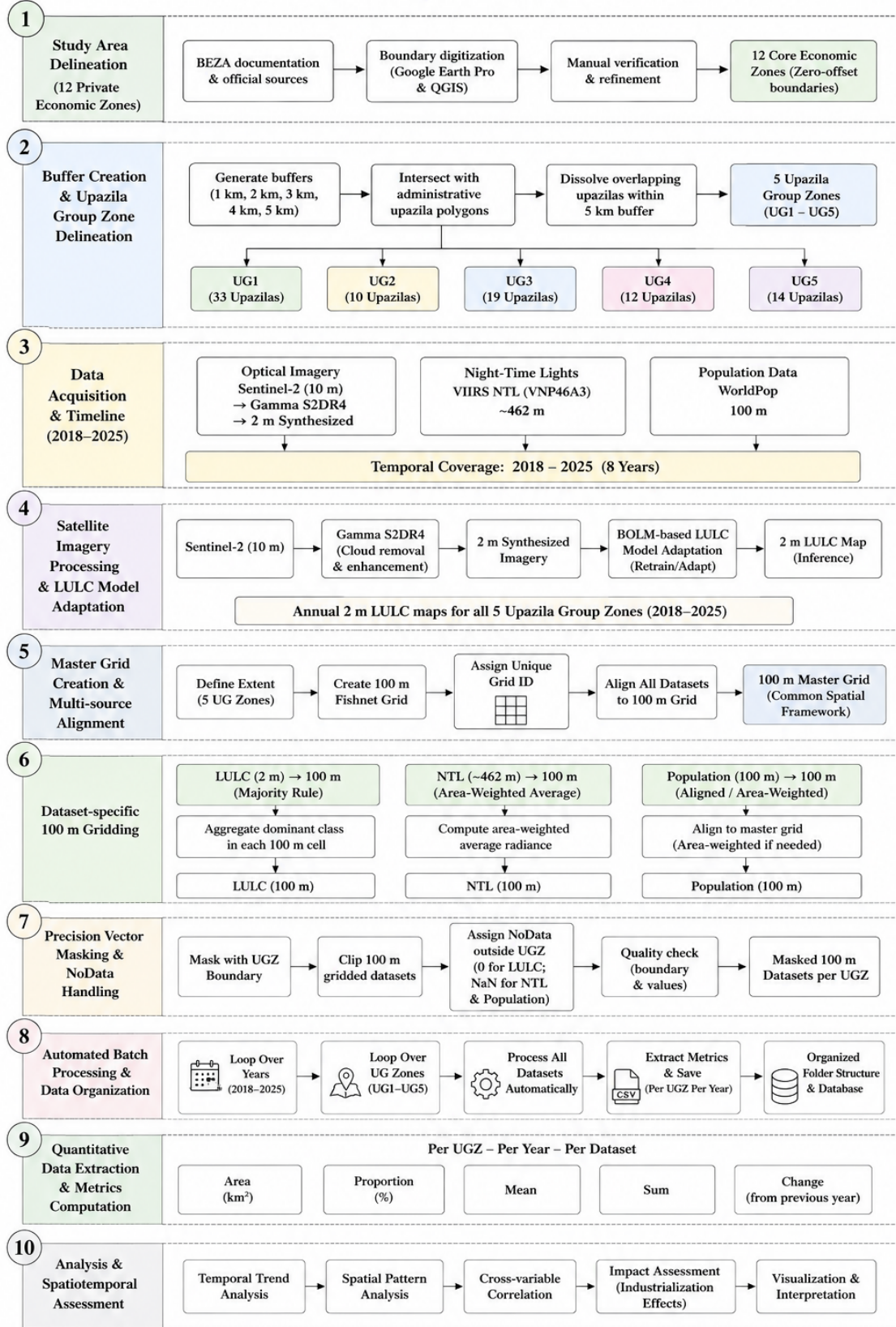


Figure 8: Detailed methodology flow diagram showing the complete sequence from study-area delineation and multi-source data acquisition through image processing, LULC adaptation, 100-m master gridding, quantitative extraction, and spatiotemporal assessment.

4.2 Software and Computational Tools

The analysis was implemented using a combination of geographic information system software, geospatial Python libraries, remote-sensing processing utilities, and deep-learning tools. The tools were selected to support vector preparation, raster processing, model inference, spatial harmonization, quality control, quantitative extraction, and visualization. The computational environment was used primarily through Python-based scripts and notebook workflows, while QGIS and Google Earth Pro were used for spatial inspection and manual boundary verification.

Table 7: Software and computational tools used in the research workflow.

Software / tool	Use in the research workflow
QGIS	Manual boundary digitization, vector inspection, buffer creation, dissolve and intersection operations, and spatial verification.
Google Earth Pro	High-resolution visual inspection and cross-checking of economic-zone boundaries against available source maps and site information.
Python	Main computational environment for automated acquisition, raster processing, quality assurance, geospatial transformation, model preprocessing, extraction, and data organization.
GDAL	Raster reading/writing, reprojection, warping, BigTIFF generation, and geospatial transformation operations.
Rasterio	Raster masking, reprojection, resampling, windowed reading, GeoTIFF processing, and extraction of geospatial raster arrays.
GeoPandas / Shapely	Vector geometry handling, spatial intersections, bounding-box generation, and geometric matching operations.
NumPy	Array manipulation, pixel-wise masking, class encoding, statistical calculations, and numerical processing.
Pandas	Tabular organization, merging, sorting, cleaning, and export of extracted annual metrics.
Gamma S2DR4	Deep-learning-based super-resolution processing used to generate the synthesized high-resolution optical imagery from Sentinel-2 observations.
UniMatchV2 / BOLM-based LULC workflow	Deep-learning LULC model framework and adaptation used for generating annual categorical LULC inference from the high-resolution optical imagery.

4.3 Spatial Boundary Delineation

The spatial boundary preparation was performed before large-scale raster acquisition so that every subsequent dataset could be processed against a consistent and reusable spatial framework. The exact boundaries of the twelve Private Economic Zones were treated as the primary analytical footprints. The surrounding buffers, intersecting Upazilas, and Upazila Group (UG) Zones were prepared as supporting spatial infrastructure and acquisition supersets rather than as the primary result units.

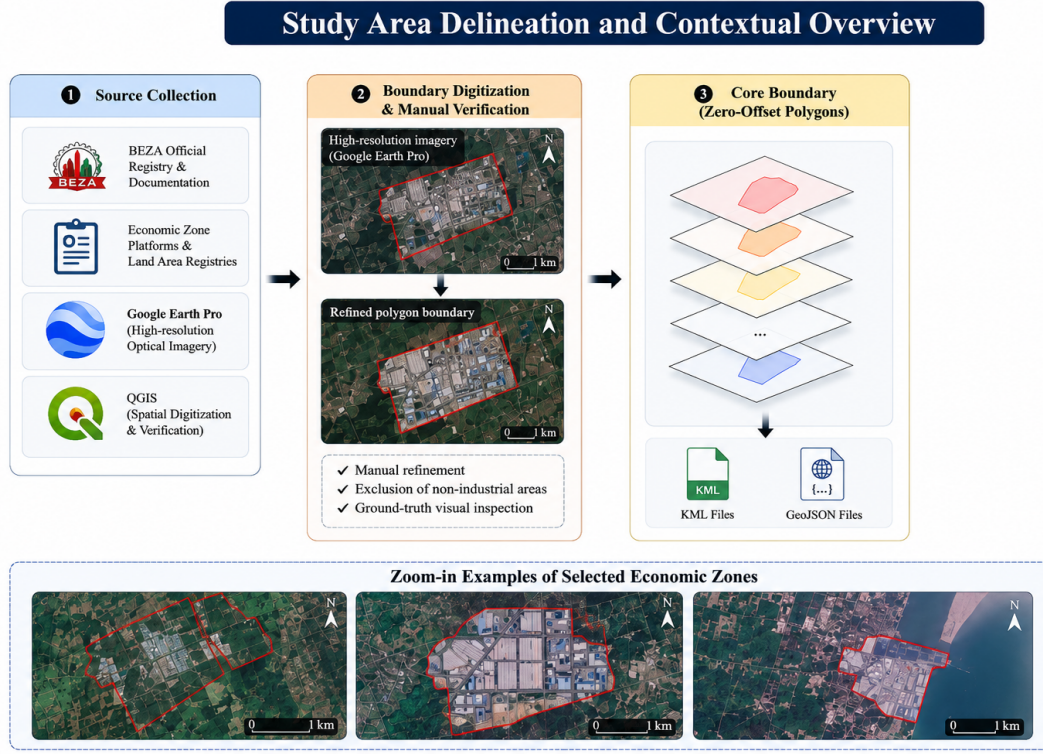


Figure 3.1: Study area delineation workflow and spatial representation of the 12 private economic zones in Bangladesh.

Figure 9: Study-area delineation and contextual overview. Official source information is followed by boundary digitization and manual verification using high-resolution imagery, producing the zero-offset polygon boundaries used for the spatial analysis. The lower panels provide representative zoom-in examples of selected economic zones.

Figure 9 provides a visual summary of the boundary-preparation procedure. The detailed geographic description of the twelve selected zones is given in Chapter 3, whereas the present section documents how the analytical geometries were prepared.

4.3.1 Zero-Offset Boundary Digitization and Verification

Because ready-to-use, high-precision vector files for the selected private economic zones were largely unavailable in public geospatial repositories, the zone boundaries were prepared manually. Official maps and documentation from the Bangladesh Economic Zones Authority and available zone-specific sources were cross-referenced with high-resolution imagery, site information, listed industries, land-area information, and other available spatial evidence. Google Earth Pro and QGIS were used to inspect the geographic setting and manually trace the physical limits of each economic zone.

The resulting polygons were refined to exclude peripheral areas that did not correspond to the intended economic-zone footprint. The final geometries were stored in Keyhole Markup Language (KML) and GeoJSON formats. The polygons were subsequently checked visually in QGIS and computationally using the project geospatial-processing scripts. These verified zero-offset polygons formed the source geometries from which all surrounding spatial extents were generated.

4.3.2 Multi-Scalar Buffer Generation and Upazila Group (UG) Zone Construction

To prepare a reusable spatial framework for future analysis of surrounding urbanization and potential spillover, concentric buffers were generated outward from the exact boundary

edge of each economic zone. Fixed-distance buffers were created at 1, 2, 3, 4, and 5 km. The 5-km buffer was retained as the principal surrounding extent for the broader project because it provides a consistent macro-scale envelope around the core economic zones.

Several economic zones are geographically close to one another, particularly within the Narayanganj and Munshiganj areas. Their 5-km buffers therefore overlap. If those overlapping buffers were processed independently, the same geographic areas could be downloaded and processed repeatedly. To avoid this redundancy, a geometric dissolve operation was applied to overlapping 5-km buffers, producing continuous non-overlapping geometries.

The dissolved 5-km buffer geometries were then intersected with the Bangladesh administrative Upazila boundaries. Upazilas falling within the relevant dissolved buffer extents were grouped according to their spatial contiguity, producing five Upazila Group (UG) Zones: UG1 through UG5. The resulting UG polygons were converted to GeoJSON and verified using QGIS and the Python geospatial-processing environment. Distinct Upazila geometries were also derived from the UG Zone framework for later use.

The five UG Zones served as the largest reusable spatial supersets for the satellite-data acquisition stage. Their purpose was computational efficiency: by acquiring and processing imagery for a UG Zone once, the constituent economic zones and their surrounding prepared spatial areas could be supported without repeatedly downloading overlapping coverage. The same framework remains available for future regional or spillover analysis. Importantly, the results presented in this thesis are restricted to the exact zero-offset boundaries of the twelve economic zones.

4.4 Satellite Data Acquisition and Processing

To conduct a robust spatiotemporal analysis of urban expansion and land-cover changes between 2018 and 2025, a multimodal data-acquisition strategy was formulated. This strategy required the synthesis of optical satellite imagery, nighttime-light radiance measurements, and demographic density distributions. The following subsections detail the computational methodologies utilized to extract, validate, and standardize these diverse datasets.

4.4.1 High-Resolution Satellite Imagery Acquisition via the Gamma S2DR4 Pipeline

The primary optical data for this study required a spatial resolution capable of detecting fine-scale industrial infrastructure and residential developments. Previous studies within this research framework successfully utilized 2.2-m resolution imagery derived from Bing SasPlanet data to train deep-learning LULC models. To maintain inferential consistency without incurring the prohibitive financial costs and stringent monthly quota limitations associated with commercial providers such as PlanetScope, an alternative high-resolution acquisition pipeline was engineered.

The research employed a deep-learning-based super-resolution inference engine known as Gamma S2DR4. This computational model mathematically upscales the native 10-m multispectral bands of Sentinel-2 Level-2A surface-reflectance imagery to a 2-m spatial resolution. To systematically process this imagery across the selected Upazila Group (UG) Zones, a mathematically deterministic geospatial grid was programmed using the Python environment. The coordinate reference system (CRS) of all input vector data was strictly transformed to the World Geodetic System (EPSG:4326).

The spatial extent of each cluster was determined by extracting the absolute bounding-box coordinates consisting of minimum and maximum longitude and latitude values. A dynamic grid was subsequently superimposed over this bounding box using a predefined spatial increment of 0.034° , which roughly translates to a 4×4 -km footprint per satellite tile. The longitudinal and latitudinal arrays were calculated as follows:

$$X_{\text{points}} = \left[Lon_{\min} - \frac{STEP}{2}, \dots, Lon_{\max} + STEP \right]. \quad (4.1)$$

$$Y_{\text{points}} = \left[Lat_{\min} - \frac{STEP}{2}, \dots, Lat_{\max} + STEP \right]. \quad (4.2)$$

For each coordinate pair in the resulting Cartesian product, a virtual bounding box was generated. A strict intersection algorithm using the Shapely computational-geometry library was applied to filter out grid squares that fell entirely outside the Upazila polygon. This filtering ensured that computational resources and download quotas were exclusively allocated to relevant terrestrial targets.

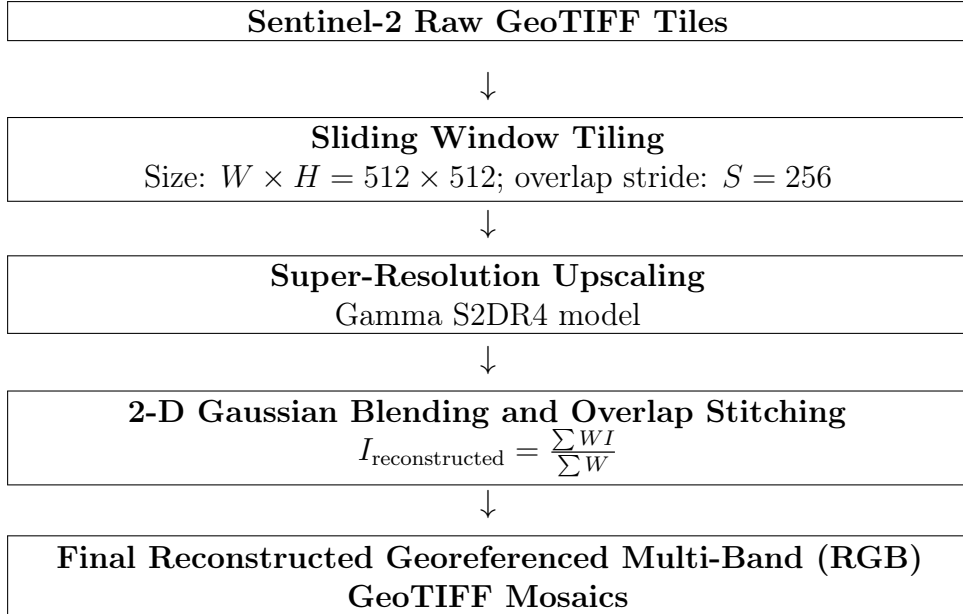


Figure 10: Processing workflow for Sentinel-2 imagery using the Gamma S2DR4 super-resolution pipeline.

A rigorous and dynamically adapting temporal-filtering mechanism was established to address the persistent challenge of monsoonal cloud cover in Bangladesh. The acquisition pipeline was programmed to exclusively target the regional dry season, iterating through an array of fallback dates spanning January to April and November to December. Furthermore, a chronological heuristic was embedded to account for the historical limitations of the Copernicus satellite archive. Because the systematic global production of Sentinel-2 Level-2A data was not fully operationalized until December 2018, traditional retrospective queries for early 2018 yield empty matrices and trigger application programming interface (API) crashes indicating that the maximum iterable argument is empty. To bypass this limitation for the 2018 dataset, the algorithm was explicitly designed to execute a forward-looking temporal shift. It dynamically extracted the nearest available clear-sky imagery from November 2018 through March 2019 to construct the 2018 spatial baseline. Deep-water oceanic tiles that inherently lack Level-2A surface processing were mathematically identified via these empty-iterable exceptions and systematically excluded from the queue.

Given the susceptibility of deep-learning super-resolution models to input anomalies, a dual-tier automated quality-assurance protocol was integrated directly into the downloading pipeline. This mechanism evaluated both the raw input and the generated output to prevent the propagation of corrupted data. Sentinel-2 operates along specific orbital swaths. When a 4×4 -km spatial grid intersects the absolute boundary of a satellite swath, the resulting image contains a distinct data void of pure black space. Super-resolution models inherently struggle with sharp null-data boundaries and frequently hallucinate false terrestrial patterns over these voids. To intercept this error, the algorithm opened the raw input array and calculated the proportion of absolute zero-value pixels. If this proportion exceeded a strict threshold of 1.0%, the tile was classified as a swath-edge anomaly and immediately discarded.

Similarly, saturated pixels caused by heavy cloud reflectance can induce nonlinear instability within the super-resolution matrices, occasionally generating localized and hypersaturated red or yellow artifacts. A threshold-based filtering algorithm was applied to the resulting three-band red, green, and blue tensor of the final outputs. The percentage of artifact-corrupted pixels and cloud-overwashed pixels were calculated globally across the spatial matrix using the following logical conditions:

$$P_{\text{artifact}} = \frac{\sum (R > 200 \wedge G < 100 \wedge B < 100)}{N_{\text{pixels}}} \times 100. \quad (4.3)$$

$$P_{\text{cloud}} = \frac{\sum (R > 220 \wedge G > 220 \wedge B > 220)}{N_{\text{pixels}}} \times 100. \quad (4.4)$$

Images exceeding a 0.5% threshold for artifact corruption or a 5.0% threshold for cloud overwash were systematically rejected. Validated images that successfully passed all heuristic checks were subsequently downsampled from the model-native 1-m output to the standardized 2-m resolution. This was achieved using the Lanczos resampling algorithm accompanied by a proportional halving of the affine geotransform matrix to ensure sub-pixel coordinate integrity.

To ensure perfect spatial continuity, a supplementary missing-tile hunting algorithm was developed. This script spatially scanned the directory of successfully downloaded images, extracted their exact center coordinates, and overlaid them against the required mathematical grid. Using Euclidean-distance matching with a high-precision tolerance, any grid coordinate lacking a corresponding downloaded tile was flagged. The pipeline then executed targeted downloads exclusively for these missing geographic gaps, iterating through the temporal fallback array until 100% terrestrial coverage was achieved for every Upazila Group (UG) Zone.

4.4.2 Spatial Mosaicking and Universal Reprojection

The integration of thousands of individual high-resolution tiles into contiguous national/UG-zone mosaics required advanced handling of cartographic projections. The geographic landmass of Bangladesh is bisected by the 90° East longitude meridian. This division places the western territories of the country in Universal Transverse Mercator Zone 45N and the eastern territories in Universal Transverse Mercator Zone 46N. Standard virtual raster-building techniques natively adopt the CRS of the initial input file encountered in the directory. This behavior causes severe spatial dislocation when tiles from the opposing zone are introduced to the mosaic, frequently resulting in massive black gaps or the complete structural failure of the merged output.

To permanently resolve this geodetic conflict, a universal reprojection methodology was executed utilizing the Geospatial Data Abstraction Library (GDAL). Instead of sequential

appending, all validated tiles, including both the original batch and the algorithmically recovered missing tiles, were ingested simultaneously into the warping engine. The entire regional mosaic was mathematically forced into the WGS 84 Pseudo-Mercator projection, recognized officially as EPSG:3857, utilizing bilinear interpolation.

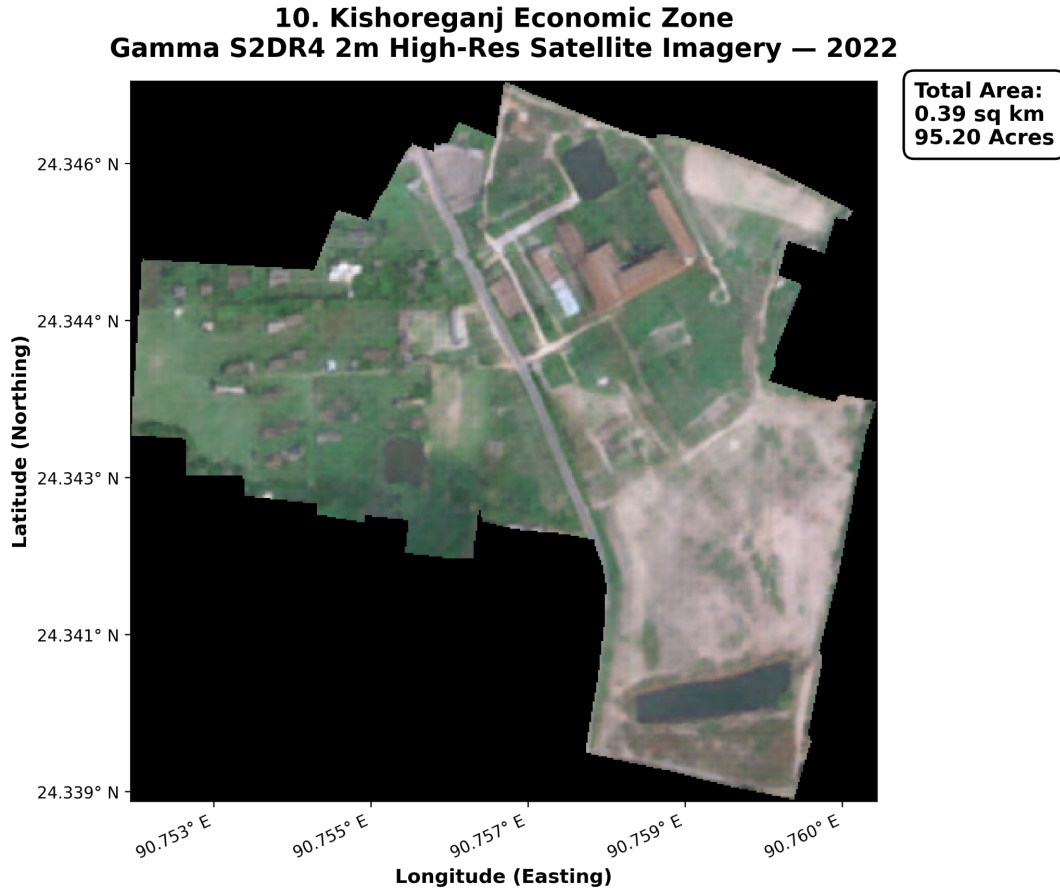


Figure 11: Representative 2-m Gamma S2DR4 optical satellite product used in the study. The sample illustrates the synthesized high-resolution imagery used as the input for the downstream LULC classification workflow.

Figure 11 provides a representative visual example of the actual 2-m optical data product used in the research.

To handle the massive computational load associated with rendering 2-m spatial resolution across entire subdistricts, the warping process was executed using maximum central-processing-unit threading. The creation options were strictly defined to generate a continuous BigTIFF format configured with internal tiling and Deflate lossless compression. The source and destination NoData values were explicitly assigned to zero. This parameterization ensured that the irregular black boundaries of overlapping satellite swaths did not overwrite valid terrestrial data from adjacent arrays during the blending process.

The final phase of the satellite-imagery pipeline involved extracting the exact Upazila Group (UG) Zone footprints from the continuously warped regional mosaics. The raw bounding-box mosaic was subjected to a highly constrained geometric clipping operation using the Python `rasterio.mask` module. The regional coordinate system was cross-validated against the original GeoJSON boundary definitions to guarantee spatial alignment prior to extraction. The raster was clipped utilizing a cropping parameter to strictly bind the matrix dimensions to the physical limits of the vector polygon, thereby substantially reducing unnecessary file weight. To ensure optimal compatibility with external geographic information system software, the metadata of the output file was modified to explicitly

declare the photometric interpretation as RGB, and the native NoData tags were scrubbed from the header post-clipping to prevent software rendering bugs. The resulting arrays were written to disk, yielding a seamless and perfectly bounded 2-m resolution satellite mosaic ready for downstream classification.

4.4.3 Nighttime Lights Radiance Data Extraction

To complement the optical satellite imagery with empirical indicators of human activity and industrial electricity consumption, Nighttime Lights radiance data were acquired. The research utilized the NASA Earthdata VIIRS NPP Lunar BRDF-Adjusted Nighttime Lights Monthly L3 Global 15 arc-second Linear Lat/Lon Grid V2 dataset, officially cataloged as VNP46A3. This specific dataset was selected due to its algorithmic correction for lunar illumination and atmospheric scattering, providing a reliable measurement of artificial radiance emitted from the Earth’s surface.

Data acquisition was performed manually via the NASA Earthdata search portal, targeting specific dry-season months corresponding to the analytical years. The spatial domain was filtered using a custom polygon encompassing the national borders of Bangladesh, resulting in the retrieval of two distinct orbital tiles per month in Hierarchical Data Format version 5 (HDF5).

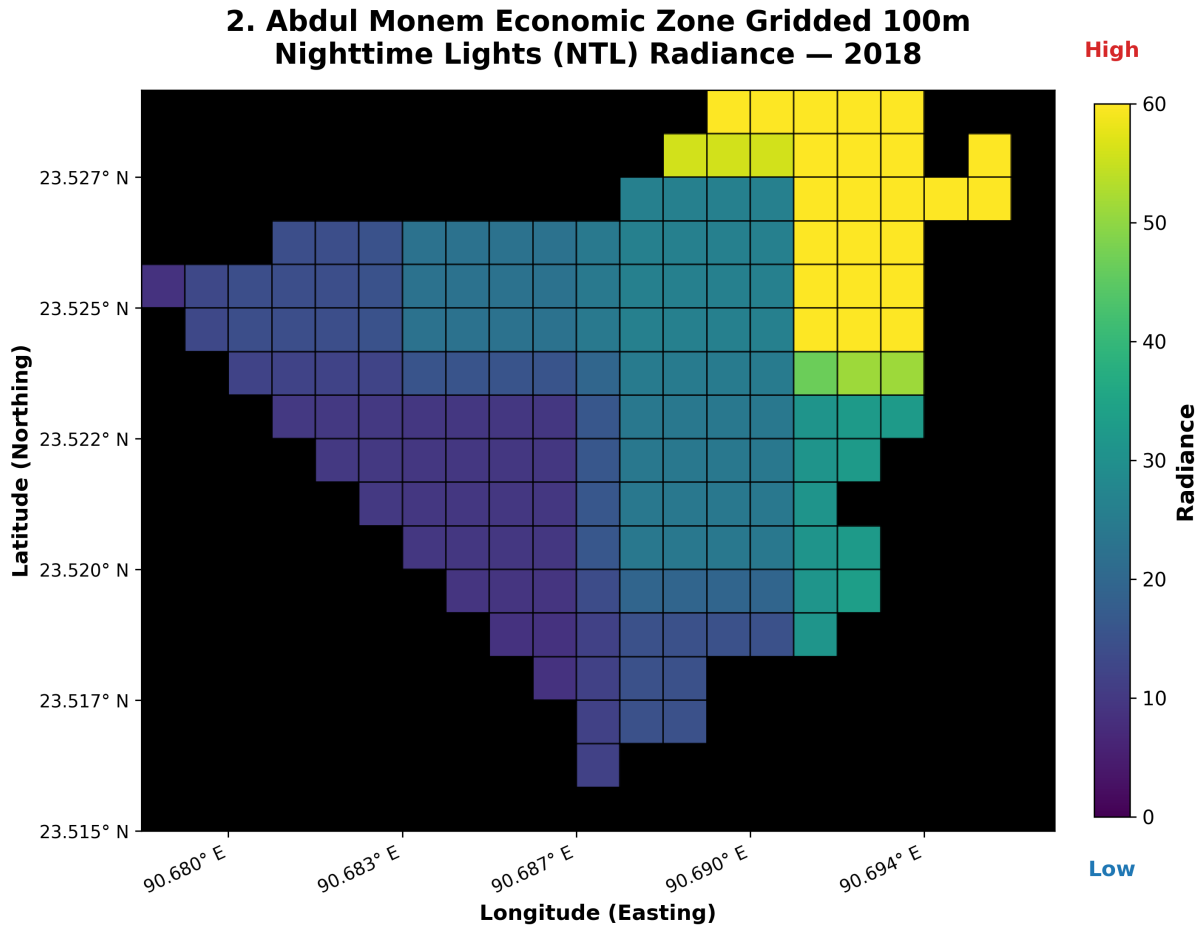


Figure 12: Example Abdul Monem Economic Zone grid 100m/px nighttime-light radiance visualization (2018), illustrating the spatial distribution of VIIRS NTL intensity used as a proxy for anthropogenic activity and industrialization.

A custom Python processing architecture was developed to translate the complex hierarchical structures into accessible geospatial rasters. The code computationally extracted

the absolute radiance array alongside the corresponding latitudinal and longitudinal grids. The numerical array was cleansed of negative algorithmic background noise by converting all values below zero into Not-a-Number (NaN) designations. An affine transformation matrix was calculated using the minimum and maximum coordinate bounds, and the clean array was exported as a GeoTIFF projected in the standard WGS 84 coordinate system.

To align the Nighttime Lights data with the highly precise population matrices, a standardized spatial-gridding methodology was implemented. The native 15 arc-second resolution, roughly equivalent to 450 m at the equator, was mathematically resampled to a strict 100×100 -m pixel grid. To preserve the physical integrity of the radiance flux during this downscaling process, an area-weighted average resampling technique was enforced via the rasterio warping module.

A master transformation function was engineered to ensure that every pixel in the Nighttime Lights matrix perfectly aligned with the target Upazila Group (UG) Zone boundaries. The bounding box of the cluster GeoJSON was mathematically snapped outward to the nearest clean 100-m interval using floor and ceiling functions. The resampled array was subsequently masked to the precise vector geometry of the cluster. For visual analytical purposes, an identically masked array was generated applying the Viridis continuous colormap, normalizing the radiance values with a maximum visual cap of $60 \text{ nW cm}^{-2} \text{ sr}^{-1}$, and converting the output into a three-band color composite. Both the raw numeric matrices and the colorized visual matrices were saved using LZW lossless compression.

4.4.4 High-Resolution Population Density Grids

Demographic distribution serves as a critical variable in assessing the urbanization impact of industrial zones. The research incorporated the WorldPop Bangladesh 100-m Population dataset Version 2.0. This dataset provides estimated numbers of people per grid square at a spatial resolution of approximately 100 m at the equator. The WorldPop methodology employs a Random Forest dasymetric modeling approach, which disaggregates national census data using a broad set of remotely sensed and ancillary geospatial covariates.

Because the native spatial resolution of the WorldPop dataset precisely matched the targeted 100-m grid requirements of this research, no complex internal interpolation or upscaling of the demographic values was necessary. The raw pixel values representing the estimated persons per grid square were strictly preserved to ensure demographic consistency.

The processing script ingested the national-level WorldPop raster and applied the identical master transformation logic utilized in the Nighttime Lights pipeline. The dataset was reprojected into the standardized EPSG:3857 Pseudo-Mercator projection. The numeric array was filtered to convert internal negative NoData designations into standard NaN representations. The national raster was then geometrically masked against the specific Upazila Group (UG) Zone GeoJSON boundaries utilizing the exact snapped transformation coordinates.

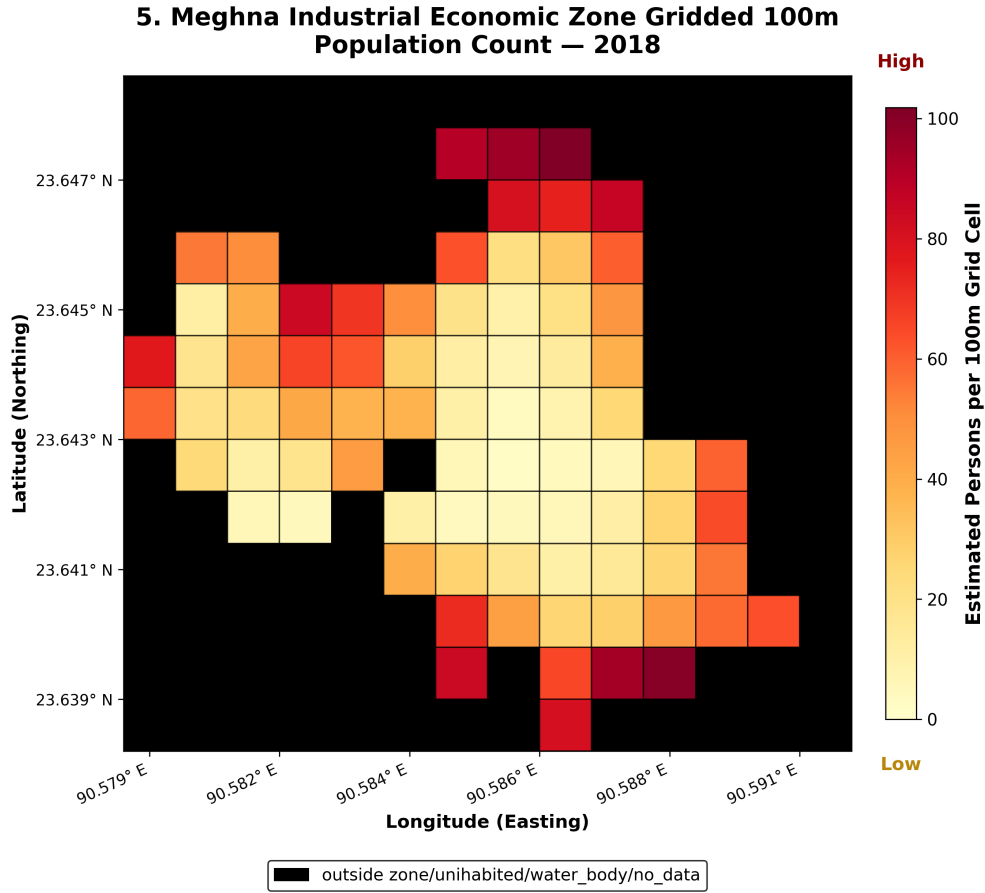


Figure 13: Example Meghna Industrial Economic Zone 100-m gridded WorldPop population visualization for 2018. Higher estimated population counts are concentrated around major urban and industrial corridors, providing the demographic layer for the multi-source analysis.

To facilitate visual interpretation of population clustering around the economic zones, a secondary colorized matrix was generated. A Yellow-to-Orange-to-Red sequential colormap was applied to the raw demographic data. The values were normalized strictly between zero and a visual maximum cap of 250 persons per pixel, ensuring that densely populated industrial-worker settlements were vividly highlighted in deep red tones. The non-spatial background was explicitly forced to pure black to maintain visual contrast. As with the preceding datasets, both the raw numeric demographic grids and the color-mapped visual grids were exported to the storage directory utilizing LZW compression, completing the comprehensive spatiotemporal data-acquisition phase of the methodology.

4.4.5 Land Use Land Cover Classification and Urban Modeling

The integration of the multi-source datasets culminated in the application of Land Use and Land Cover (LULC) classification models. The 2-m spatial resolution achieved through the Gamma S2DR4 super-resolution pipeline provided the necessary visual fidelity to distinguish between complex industrial rooftops, newly constructed road networks, bare-earth land preparations, and adjacent agricultural or vegetative boundaries. By maintaining the 2-m resolution, the research extended the deep-learning classification architecture previously validated on commercial satellite data.

The subsequent classification outputs were spatially intersected with the 100-m Night-time Lights radiance matrices and the 100-m population-density grids. This intersection enabled the formulation of composite urbanization indices entirely constrained within the absolute borders of the twelve Private Economic Zones. Utilizing this standardized

spatial and demographic framework, the study systematically quantified the magnitude of structural and human expansion over the targeted temporal period.

The primary visual and categorical data were derived from 2-m high-resolution optical satellite imagery. These datasets were initially processed using the Gamma S2DR4 pipeline to generate detailed RGB composites covering the five Upazila Group (UG) Zones. From these raw satellite inputs, categorical Land Use and Land Cover (LULC) maps were generated using the BOLM LULC model, which was retrained or adapted to the Gamma S2DR4 input imagery used in this study.

The LULC categorization utilized a six-class taxonomy: Unclassified (Class 0), Farmland (Class 1), Water (Class 2), Forest (Class 3), Built-up (Class 4), and Meadow (Class 5). To ensure rigorous model comparison and mitigate data collision, the classification outputs from three distinct model training checkpoints were archived: The outputs generated via the UniMatchV2 semi-supervised learning architecture. We will discuss about the LULC Classification and training in the subsequent sections.

4.5 Deep Learning Data Preprocessing and LULC Model Adaptation

The preparation of high-resolution remote-sensing datasets for deep-learning applications required rigorous spatial and semantic harmonization. The present LULC workflow was derived from the Bangladesh Open LULC Map (BOLM) framework, which provides high-resolution pixel-level reference data and benchmark experiments for Bangladesh [3]. The original reference imagery differs from the Gamma S2DR4 optical product used in this study; therefore, the BOLM training material was spatially and semantically prepared before model adaptation. The preprocessing objective was to ensure pixel-to-pixel correspondence between the satellite imagery and labeled masks while preserving the original geographic structure of the data.

The preprocessing pipeline consisted of spatial harmonization and masking, semantic class encoding, and high-fidelity sliding-window patch generation. The resulting prepared patches were then used for model adaptation and subsequent annual LULC inference.

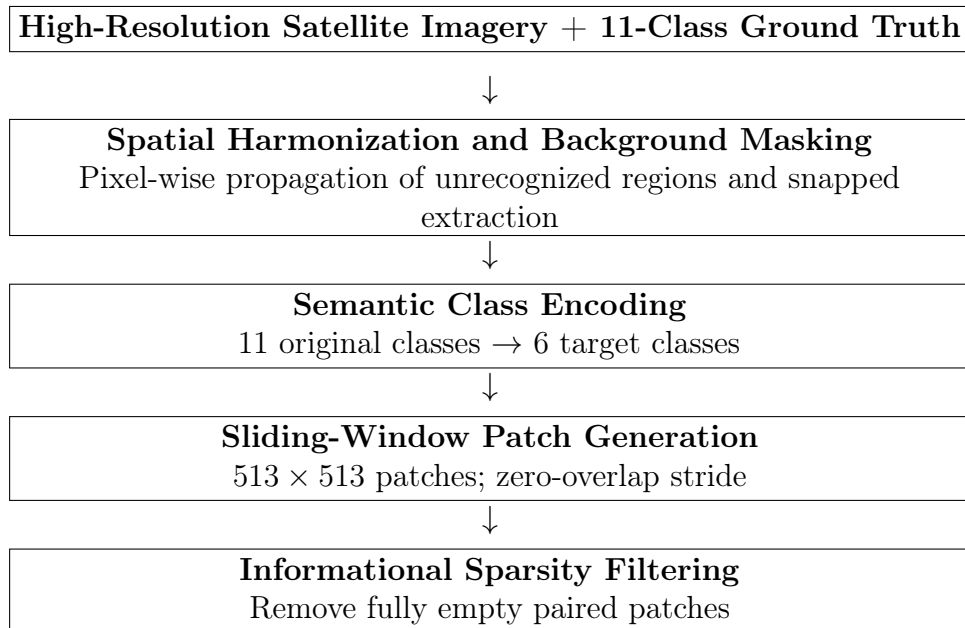


Figure 14: Deep-learning LULC preprocessing workflow from the high-resolution image and labeled ground-truth data to the prepared training and validation patches.

4.5.1 Spatial Harmonization and Background Masking

Raw satellite imagery contains regions with missing or invalid data, often represented by background collars or unrecognized areas. In the utilized ground-truth masks, ambiguous or temporally inconsistent regions were explicitly designated as the “Unrecognized” class and encoded with the RGB vector $(0, 0, 0)$. To prevent the deep-learning model from learning from these unverified regions, a pixel-wise masking algorithm propagated the ground-truth background pixels into the corresponding satellite input.

The algorithm reads the satellite imagery and the corresponding ground-truth mask into multidimensional arrays and evaluates every spatial location (x, y) . The masking function is defined as:

$$M(x, y) = \begin{cases} \text{True}, & \text{if } GT(x, y) = (0, 0, 0), \\ \text{False}, & \text{otherwise.} \end{cases} \quad (4.5)$$

For every pixel where $M(x, y)$ is true, the corresponding satellite input pixel is forced to the null vector $(0, 0, 0)$. The masking was performed sequentially, first using the full regional ground-truth mask and then using the training-specific mask. This dual masking ensured that the final training input followed the spatial distribution of valid labeled information and excluded unrecognized regions from model learning.

4.5.2 Targeted Validation Extraction and Snapped Alignment

Extracting a clean validation subset from a contiguous multi-gigabyte raster was complicated by large NoData collars surrounding portions of the source imagery. A vector-guided extraction approach was therefore adopted. A GeoJSON polygon was used to loosely delimit the target validation region, after which its geographic extent was transformed into raster pixel coordinates using the master geotransform.

Within this localized search window, row- and column-wise background counts were evaluated. A threshold of 50 percent of the maximum row and column background counts was used to isolate the densest contiguous background structure and to determine the extraction window required for the validation subset. This avoided incorporating irrelevant outer collars into the extracted validation data.

Because floating-point metadata differences can introduce sub-pixel offsets between otherwise corresponding rasters, a snapped extraction procedure was also applied. Resampling was deliberately avoided for categorical ground-truth labels at this stage. The starting pixel positions were calculated by rounding the geographic coordinates to the integer pixel coordinates of the master raster:

$$P_{x_{\min}} = \text{round} \left(\frac{X_{\min} - GT_{\text{master}}[0]}{GT_{\text{master}}[1]} \right), \quad (4.6)$$

$$P_{y_{\min}} = \text{round} \left(\frac{Y_{\max} - GT_{\text{master}}[3]}{GT_{\text{master}}[5]} \right). \quad (4.7)$$

Here, $X_{\min}$ and $Y_{\max}$ represent the geographic top-left coordinates of the target bounding box, while $GT_{\text{master}}[0]$ and $GT_{\text{master}}[3]$ are the geographic top-left coordinates of the master raster and $GT_{\text{master}}[1]$ and $GT_{\text{master}}[5]$ are its pixel dimensions. The resulting pixel window was extracted directly from the master raster so that the input and label arrays remained pin-to-pin aligned.

4.5.3 Semantic Class Encoding and Aggregation

The original BOLM labels contain eleven detailed high-resolution land-cover categories. For the present adaptation, the detailed classes were consolidated into six target classes to reduce severe class imbalance and to provide a consistent category definition for model training. The six target classes were Unclassified, Farmland, Water, Forest, Built-up, and Meadow.

The original classes Urban Structure, Rural Built-Up, Urban Built-Up, Road, and Brick Factory were grouped into the Built-up class. Marshland and Meadow were grouped into the Meadow class. Background, Farmland, Water, and Forest were retained as their corresponding target categories. Table 8 summarizes the semantic mapping used in the preprocessing stage.

Table 8: Semantic class encoding and aggregation from the eleven original LULC categories to six target classes.

Original class	Original RGB	Target class	Target RGB
Background	(0, 0, 0)	Unclassified	(0, 0, 0)
Urban Structure	(128, 0, 0)	Built-up	(255, 0, 0)
Rural Built-Up	(255, 0, 255)	Built-up	(255, 0, 0)
Urban Built-Up	(255, 0, 0)	Built-up	(255, 0, 0)
Road	(160, 160, 164)	Built-up	(255, 0, 0)
Brick Factory	(128, 0, 128)	Built-up	(255, 0, 0)
Farmland	(0, 255, 0)	Farmland	(0, 255, 0)
Water	(0, 0, 255)	Water	(0, 0, 255)
Forest	(0, 255, 255)	Forest	(0, 255, 255)
Marshland	(255, 251, 240)	Meadow	(255, 255, 0)
Meadow	(255, 255, 0)	Meadow	(255, 255, 0)

The encoding was implemented through array-based pixel mapping. The raster data were transposed into a height-width-channel configuration, after which a dictionary lookup matched the original RGB tuples to their target class representations. Boolean masks isolated matching pixels and the aggregate RGB vector was broadcast to the selected positions. The encoded raster inherited the spatial metadata of the input file, preserving geographic fidelity.

4.5.4 High-Fidelity Sliding-Window Patch Generation

Because the full high-resolution raster is too large to be processed as a single training tensor, the paired satellite and ground-truth arrays were parsed into uniform patches. A dual-read sliding-window algorithm traversed the input and label arrays simultaneously using a patch dimension of $P = 513$ pixels and a stride of $S = 513$ pixels. The zero-overlap configuration reduced spatial duplication and helped prevent redundant neighboring patches during training.

The spatial window for iteration (i, j) was defined as:

$$W_{i,j} = I[iS : iS + P, jS : jS + P]. \quad (4.8)$$

Any edge window whose width or height was less than P was rejected so that only dimensionally complete 513×513 patches entered the prepared dataset.

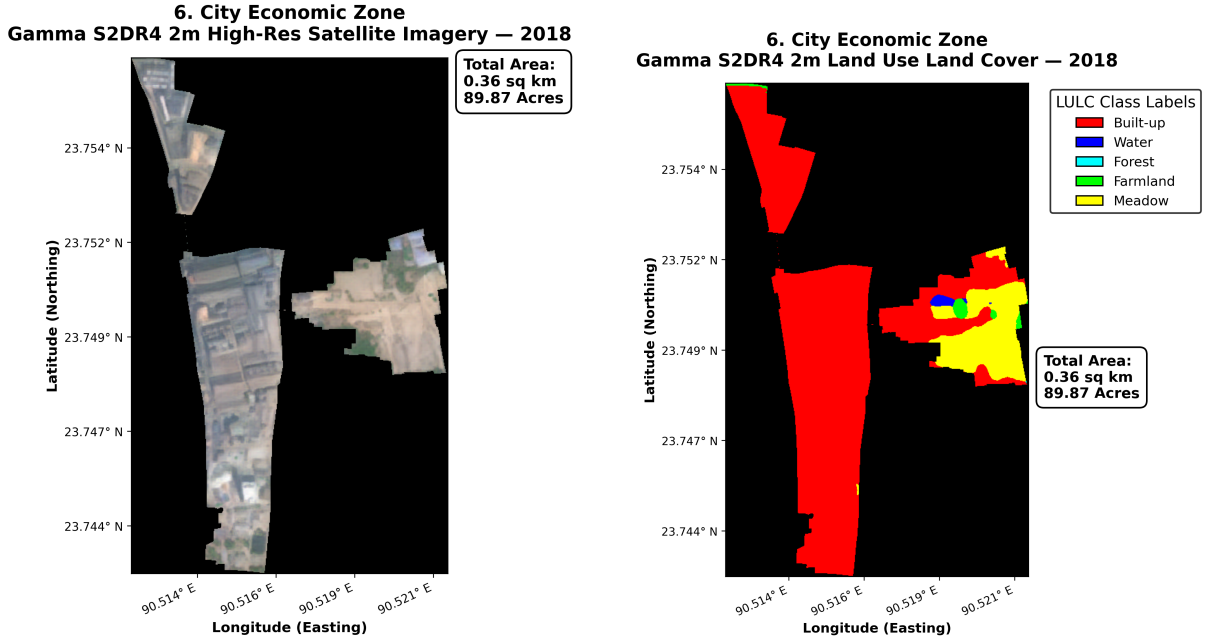
Because extensive masked or unrecognized regions existed in the source data, an informational sparsity filter was applied. For a three-channel patch, the sparsity check was defined as:

$$SparsityCheck = \sum_{c=1}^3 \sum_{x=1}^{513} \sum_{y=1}^{513} W_{c,x,y}. \quad (4.9)$$

If the sparsity check equaled zero for either the satellite input patch or its corresponding ground-truth mask, the paired files were moved to a skipped directory. Valid patches were exported to the active training or validation directories, with their coordinate transform recalculated for the specific patch footprint.

4.5.5 LULC Model Adaptation and Annual Inference

The prepared dataset was used to adapt the BOLM-based LULC workflow to the Gamma S2DR4 optical input. This step was necessary because the present study uses synthesized high-resolution RGB imagery rather than the original Bing imagery employed by the BOLM reference dataset [3]. The model configuration used in the project includes the UniMatchV2-based semantic-segmentation workflow identified during the model adaptation stage.



(a) 2-m Gamma S2DR4 optical imagery for the sample zone.

(b) Corresponding five-class LULC inference at 2-m resolution.

Figure 15: Representative example of the annual LULC inference workflow for the City Economic Zone in 2018 within the extended 5-km contextual extent. Panel (a) shows the corresponding 2-m Gamma S2DR4 optical input, while panel (b) shows the resulting five-class LULC inference comprising Built-up, Water, Forest, Farmland, and Meadow.

As a representative case, Figure 15 illustrates the relationship between the high-resolution optical input and the corresponding annual LULC inference for the City Economic Zone in 2018 within the extended 5-km contextual extent.

Following preprocessing and model adaptation, full-scale LULC inference was carried out over the prepared high-resolution satellite coverage for each year from 2018 to 2025. The resulting categorical maps were stored at 2-m analytical resolution. For the subsequent

multi-source analysis, the annual LULC classes were reduced to the five reported classes used in the results: Farmland, Water, Forest, Built-up, and Meadow. The Unclassified/background class was retained only for masking and data-quality handling and was excluded from the reported recognized-class composition.

4.6 Automated Image Validation and Quality Assurance

The utilization of deep-learning architectures for spatial super-resolution, specifically the Gamma S2DR4 model, introduces unique methodological vulnerabilities. Neural networks trained to upscale 10-m native Sentinel-2 optical bands to a 2-m resolution are highly sensitive to input anomalies. When presented with irregular atmospheric reflectance or absolute data voids, the underlying matrices frequently overcompensate, resulting in the generation of false topological features or hypersaturated visual artifacts. To prevent these computational errors from corrupting the subsequent Land Use and Land Cover (LULC) classification algorithms, a dual-tier automated quality-assurance and validation protocol was engineered directly into the data-acquisition pipeline. This algorithmic filter evaluates both the native Level-2A input arrays and the super-resolved outputs prior to local storage.

4.6.1 Swath Edge Detection and NoData Exclusion

The Sentinel-2 satellite constellation captures optical data along distinct orbital trajectories known as swaths. Because the terrestrial surface is captured in diagonal strips, the rigid boundaries of the mathematically generated spatial grid frequently intersect the absolute limits of a given orbital pass. The predefined spatial grid utilized a step-size increment of 0.034° . In the context of the World Geodetic System (EPSG:4326), one longitudinal degree near the equator equates to approximately 111 km. Consequently, the 0.034° increment translates to a localized footprint of approximately 4×4 km per generated tile.

When one of these 4×4 -km grid boxes falls partially off the edge of a satellite swath, the missing spatial data are recorded by the sensor as an absolute data void. In digital image processing, these voids are represented by a Digital Number (DN) of absolute zero. If fed into the super-resolution model, the algorithm attempts to interpret this pure black space as physical terrain, hallucinating dark green or brown topological noise.

To intercept this structural error, the validation algorithm intercepts the raw Level-2A input matrix prior to the super-resolution inference. The system isolates the primary optical band and calculates the proportion of zero-value pixels against the total pixel count of the spatial matrix.

Let A_{raw} represent the single-band raw input matrix, N_{total} represent the total number of pixels within the matrix, and N_{zero} represent the aggregate count of pixels where the condition $DN = 0$ is satisfied. The percentage of swath-edge data void, denoted as P_{void} , is calculated using Equation (4.10):

$$P_{\text{void}} = \left(\frac{N_{\text{zero}}}{N_{\text{total}}} \right) \times 100. \quad (4.10)$$

To ensure that valid terrestrial shadows or natural dark water bodies are not erroneously classified as data voids, an empirical tolerance threshold was established. If the calculated P_{void} exceeds 1.0%, the respective tile is officially classified as a swath-edge anomaly. The algorithm immediately discards the corrupted file and triggers the temporal fallback mechanism to locate a continuous, edge-to-edge image from a different orbital pass within the targeted dry-season parameters.

4.6.2 Cloud Overwash and Algorithmic Artifact Filtration

The second tier of the quality-assurance protocol addresses atmospheric interference. Thick cumulus cloud cover acts as a highly reflective surface, saturating the optical sensors of the satellite. When these oversaturated, pure-white pixel arrays are processed by the super-resolution model, the mathematical upscaling parameters destabilize. This destabilization manifests in the final output as severe geometric distortion and localized, hypersaturated red or yellow pixel blobs, fundamentally compromising the integrity of subsequent automated land-cover classification.

To systematically filter these anomalies, a threshold-based Boolean masking algorithm was developed to analyze the final generated spatial tensor. The evaluation is performed on the three-band composite array, where R , G , and B represent the 8-bit pixel intensity values (ranging from 0 to 255) for the Red, Green, and Blue spectral bands, respectively.

The algorithm scans the output matrix to identify pixels that exhibit the unnatural spectral signatures associated with computational hallucinations. Specifically, hallucinated artifacts typically display extreme saturation in the red optical band while simultaneously recording abnormally low values in the green and blue bands. The condition for an artifact-corrupted pixel, $C_{\text{artifact}}(i)$, for any given pixel i , is mathematically defined as:

$$C_{\text{artifact}}(i) = \begin{cases} 1, & \text{if } R_i > 200, G_i < 100, B_i < 100 \\ 0, & \text{otherwise.} \end{cases} \quad (4.11)$$

Similarly, the presence of severe cloud overwash is detected by identifying pixels that demonstrate uniform, near-maximum saturation across all three optical bands, representing pure-white physical reflectance. The condition for a cloud-overwashed pixel, $C_{\text{cloud}}(i)$, is defined as:

$$C_{\text{cloud}}(i) = \begin{cases} 1, & \text{if } R_i > 220, G_i > 220, B_i > 220 \\ 0, & \text{otherwise.} \end{cases} \quad (4.12)$$

Upon evaluating every pixel within the spatial matrix, the algorithm computes the global percentage of artifact corruption (P_{artifact}) and cloud overwash (P_{cloud}) relative to the total pixel count (N_{total}) of the generated tile:

$$P_{\text{artifact}} = \left(\frac{\sum_{i=1}^{N_{\text{total}}} C_{\text{artifact}}(i)}{N_{\text{total}}} \right) \times 100. \quad (4.13)$$

$$P_{\text{cloud}} = \left(\frac{\sum_{i=1}^{N_{\text{total}}} C_{\text{cloud}}(i)}{N_{\text{total}}} \right) \times 100. \quad (4.14)$$

Based on iterative visual inspection of the model outputs, strict rejection thresholds were enforced. If a generated tile yields a P_{artifact} exceeding 0.5%, or a P_{cloud} exceeding 5.0%, the image is classified as structurally defective and deleted from local storage. Only files that successfully satisfy both the swath-edge constraints and the RGB artifact constraints are retained for integration into the final regional mosaic.

4.6.3 Targeted Missing Tile Recovery and Spatial Interpolation

Following the initial execution of the downloading pipeline, spatial integrity checks revealed that rigid reliance on standard sequential grid-generation arrays, such as the NumPy `arange` function, inherently truncates boundary coordinates. If the mathematically calculated step size does not perfectly align with the absolute eastern or northern boundary of the

GeoJSON polygon, the final edge coordinates are omitted from the processing queue. Additionally, tiles persistently rejected by the artifact-filtration protocols created internal spatial gaps within the Upazila Group (UG) Zones.

To achieve absolute spatial continuity, a secondary algorithmic sequence termed the “Targeted Gap Filler” was engineered. This methodology abandons sequential tile numbering in favor of absolute geospatial coordinate matching.

First, the original bounding box of the Upazila Group (UG) Zone is mathematically expanded outward by an additional spatial increment, *STEP_SIZE_DEG*. This expansion guarantees that the generated coordinate grid encompasses the absolute maximum physical boundaries of the administrative polygon, capturing all edge cases.

Second, the script performs a directory-level spatial scan of all previously validated and successfully downloaded *.tif* files. Utilizing the *rasterio* module, the algorithm extracts the exact physical bounding coordinates of each existing image and calculates its true central longitude and latitude.

Finally, a computational overlay is performed. The algorithm iterates through every theoretical coordinate pair required by the expanded grid and attempts to find a matching existing tile center. Let $(Lon_{target}, Lat_{target})$ represent the coordinates of the required grid position, and $(Lon_{existing}, Lat_{existing})$ represent the coordinates of an already downloaded tile. The spatial proximity is evaluated using the standard Euclidean distance formula, denoted as D :

$$D = \sqrt{(Lon_{target} - Lon_{existing})^2 + (Lat_{target} - Lat_{existing})^2}. \quad (4.15)$$

A spatial match tolerance, T_{match} , was defined as 0.01° , which corresponds to approximately 1.1 km of allowable spatial deviation. For any given target coordinate, if the condition $D \leq T_{match}$ is not satisfied by any tile in the existing directory, the specific target coordinate is officially flagged as a missing spatial gap.

The acquisition algorithm then isolates these flagged coordinates and attempts targeted downloads. To maximize the probability of retrieving clear imagery for these difficult spatial gaps, the temporal fallback parameters were aggressively expanded to include the 1st and 15th days of every month during the optimal dry season. During this secondary retrieval phase, the system frequently encountered Application Programming Interface (API) rejections yielding HTTP Status Code 500 (Internal Server Error) or “empty iterable” exceptions. The latter exception specifically occurs when the expanded geographic grid pushes the target coordinate entirely off the terrestrial landmass and into the deep ocean waters of the Bay of Bengal, where Copernicus Level-2A data are not generated. To ensure programmatic stability, the script incorporates an internal diagnostic logger that traps these specific exception strings. Coordinates returning empty iterable arrays across all temporal attempts are definitively classified as non-terrestrial ocean tiles and are permanently excluded from the spatial requirement matrix, thereby fulfilling the 100% terrestrial coverage requirement for the final mosaicking phase.

4.7 Geospatial Harmonization and the 100 Meter Master Gridding Pipeline

A fundamental challenge in modern spatial data science is the integration of multi-source datasets possessing inherently incompatible native resolutions. In this research, the spatial parameters required for urbanization analysis were derived from three distinct data sources. The land use and land cover classifications operated at a highly granular 2-m spatial

resolution. The NASA Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime-light radiance measurements were captured at an approximate 462-m spatial resolution. Concurrently, the WorldPop demographic density models were generated at a 100-m spatial resolution.

Attempting to perform pixel-by-pixel correlation or spatial regression across these three mismatched geometric grids would introduce ecological fallacies and statistical distortions. To mathematically rectify this dimensional incompatibility, a universal geospatial harmonization protocol was engineered. A 100-m by 100-m spatial grid was selected as the master resolution. This dimension was deliberately chosen to match the native resolution of the demographic dataset, thereby preventing artificial interpolation of human population counts, while allowing the optical land-cover and continuous light-flux datasets to be statistically aggregated without losing critical macroscopic patterns.

All geospatial datasets were strictly reprojected into the unified EPSG:3857 coordinate reference system, which relies on metric units and facilitates absolute distance calculations and area-specific geometric operations.

4.7.1 The Snapped Master Grid Transformation Algorithm

Standard spatial clipping tools embedded within geographic information systems frequently rely on floating-point arithmetic to determine the bounding box of a target polygon. When different datasets are cropped independently using these floating-point coordinates, microscopic sub-pixel misalignments inevitably occur. Even an alignment error of a fraction of a meter renders multi-layer tensor stacking mathematically invalid, as convolutional architectures and pixel-array calculations demand absolute vertex matching.

To eradicate this geometric distortion, a mathematical “Snapped Master Transform” algorithm was developed and integrated into the Python processing pipeline. The algorithm takes the vector boundary of a given Upazila Group (UG) Zone and calculates an absolute, integer-locked bounding box that forces every pixel edge to align perfectly with a continuous 100-m grid originating from the absolute coordinate system origin.

Let the raw geographic bounding box of the input vector polygon be defined by the minimum and maximum coordinates ($X_{\min}, Y_{\min}, X_{\max}, Y_{\max}$). The algorithm derives the snapped coordinates using:

$$X_{\text{snap_min}} = \left\lfloor \frac{X_{\min}}{100.0} \right\rfloor \times 100.0 \quad (4.16)$$

$$Y_{\text{snap_min}} = \left\lfloor \frac{Y_{\min}}{100.0} \right\rfloor \times 100.0 \quad (4.17)$$

$$X_{\text{snap_max}} = \left\lceil \frac{X_{\max}}{100.0} \right\rceil \times 100.0 \quad (4.18)$$

$$Y_{\text{snap_max}} = \left\lceil \frac{Y_{\max}}{100.0} \right\rceil \times 100.0. \quad (4.19)$$

Here, $\lfloor z \rfloor$ denotes the floor function and $\lceil z \rceil$ denotes the ceiling function. Dividing the raw coordinate by 100.0, applying the corresponding integer function, and multiplying by 100.0 forces each coordinate onto an absolute 100-m grid line.

Following the derivation of the snapped boundary, the absolute pixel dimensions of the resulting spatial matrix are:

$$W = \frac{X_{\text{snap_max}} - X_{\text{snap_min}}}{100}, \quad H = \frac{Y_{\text{snap_max}} - Y_{\text{snap_min}}}{100}. \quad (4.20)$$

These parameters are used to construct the rigid six-element affine transformation matrix that governs the translation of continuous geographic space into discrete image-pixel indices:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}. \quad (4.21)$$

The coefficient a specifies the pixel width (100.0 m), e specifies the pixel height (-100.0 m because the raster origin is at the top left), c establishes the starting X coordinate ($X_{\text{snap_min}}$), and f establishes the starting Y coordinate ($Y_{\text{snap_max}}$). The rotation coefficients b and d are maintained at zero to prevent geometric skewing. This mathematically derived affine matrix acts as the spatial anchor for the entire gridding pipeline.

4.7.2 Dataset-Specific Spatial Resampling and Gridding Algorithms

The reprojection of geospatial datasets from their native resolutions into the standard 100-m master grid required dataset-specific algorithmic resampling. Because the intrinsic properties, spatial resolutions, and data structures of the three primary datasets differ fundamentally, a singular mathematical approach could not be applied. The methodology was therefore partitioned into three distinct workflows tailored specifically for LULC, NTL, and population-density data. All datasets were strictly reprojected into EPSG:3857 during this phase.

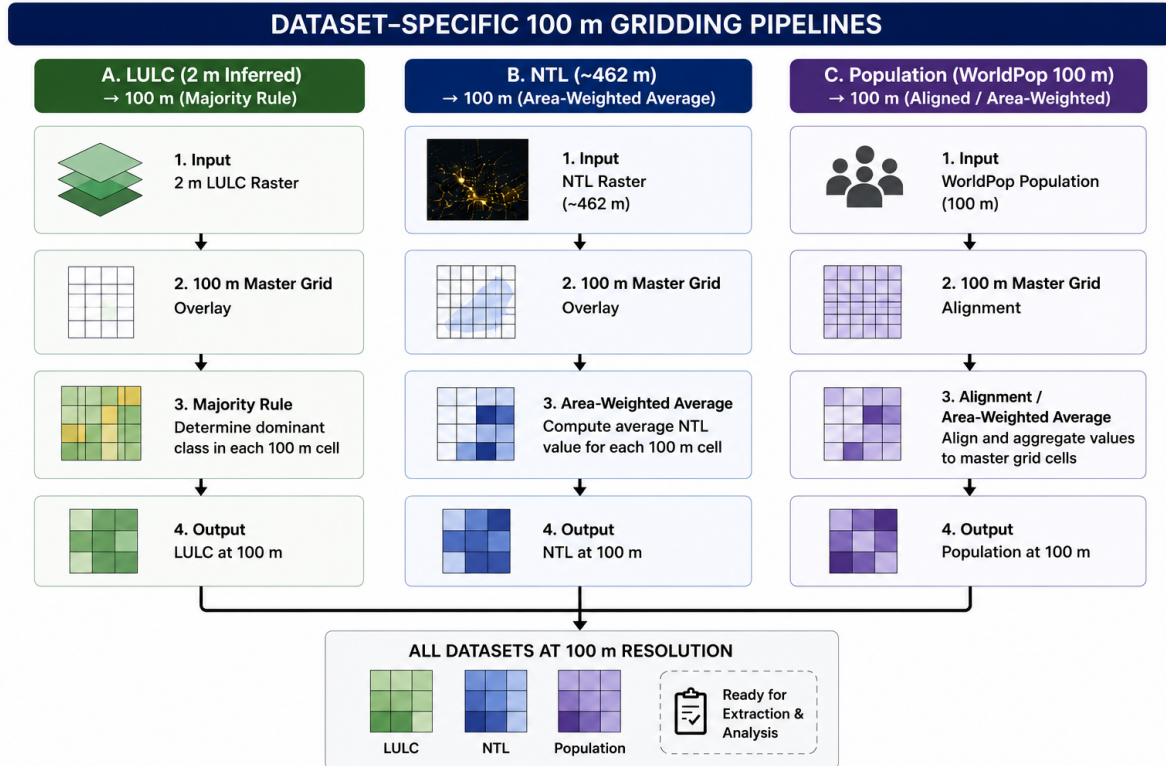


Figure 16: Dataset-specific 100-m gridding pipelines for the three principal datasets. LULC is aggregated from 2 m using a majority rule, NTL is harmonized from approximately 462 m using area-weighted averaging, and WorldPop is aligned to the same master grid at its native 100-m resolution.

100-Meter Gridding Pipeline for Land Use Land Cover (LULC) Data

The LULC data derived from the Gamma S2DR4 satellite inference operated natively at a 2-m spatial resolution and were stored as three-channel red-green-blue (RGB) raster arrays. Aggregating multi-channel color data directly into a 100-m grid using standard arithmetic averaging would corrupt the categorical classification by yielding fractional color values that do not correspond to known land-cover classes.

To preserve categorical integrity during upscaling, a multi-step dimensionality-reduction and statistical-mode (majority-rule) resampling algorithm was implemented. First, the 3-channel RGB tensor was read into computational memory and a predefined dictionary mapped RGB tuples to discrete integer class values. A boolean masking operation isolated matching RGB vectors and flattened the 3-channel image into a 1-channel, 8-bit integer array.

The spatial resampling then evaluated each 100-m by 100-m macro-pixel window delineated by the snapped master transform. Within this boundary there are exactly 2,500 underlying 2-m micro-pixels. The `rasterio.warp.reproject` function was invoked using the `Resampling.mode` parameter. The statistical mode, i.e., the most frequently occurring class integer among the 2,500 micro-pixels, was assigned to the corresponding 100-m macro-pixel.

Following spatial aggregation, the 1-channel categorical array was reconstructed into a 3-channel RGB configuration by broadcasting the original RGB vectors back into the matrix. The final array was masked against the target vector geometry, with exterior pixels forced to zero, and exported as a fully aligned 100-m gridded LULC map.

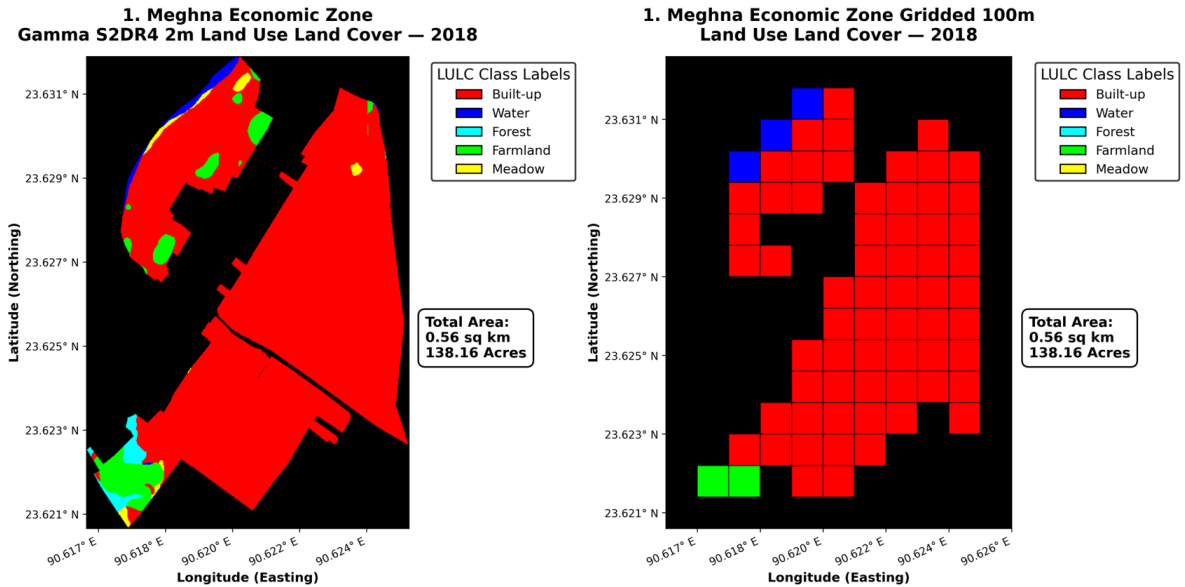


Figure 17: Illustrative LULC harmonization from the native 2-m classification to the 100-m master grid using the majority-rule resampling strategy. The example demonstrates how the dominant categorical class within each 100-m cell is retained while preserving the spatial footprint of the economic zone.

100-Meter Gridding Pipeline for Nighttime Lights (NTL) Radiance

The VIIRS NTL radiance data represent a continuous physical flux measurement operating at a native spatial resolution of approximately 462 m. Applying a categorical majority rule to this continuous distribution would erase variance and compromise the physical integrity of the radiance measurements.

Consequently, an area-weighted averaging algorithm was engineered. When the coarse 462-m pixels are transformed to the 100-m target grid, a single native NTL pixel can encompass multiple target cells. The `Resampling.average` parameter is used within the reprojection matrix. This area-weighted algorithm calculates the geometric intersection between the source-pixel footprint and the destination grid, distributing the continuous radiance flux according to the spatial percentage of overlap.

During programmatic execution, NTL arrays required specific NoData handling. Pixels outside the target boundary were explicitly assigned the NaN (Not a Number) floating-point representation to prevent exterior black space from artificially suppressing statistical means. The raw numerical flux data were saved as single-channel `float32` TIF files to preserve mathematical precision. A secondary visualization pipeline normalized the radiance data using a dynamic threshold and applied a Viridis color map to generate a corresponding RGB output for qualitative geographic assessment.

100-Meter Gridding Pipeline for Population Density (WorldPop)

The WorldPop demographic estimates natively operate at a 100-m spatial resolution. Although the nominal source resolution matched the target architecture, microscopic misalignments existed between the native WorldPop coordinates and the absolute snapped grid coordinates derived from the Upazila Group (UG) Zones.

Therefore, the population grids were forced through the same snapped affine transformation matrix used for the other datasets. Before reprojection, the raw WorldPop array was filtered so that negative NoData indicators were converted to NaN:

$$Pop_{\text{filtered}}(x, y) = \begin{cases} \text{NaN}, & \text{if } Pop_{\text{raw}}(x, y) < 0 \\ Pop_{\text{raw}}(x, y), & \text{otherwise.} \end{cases} \quad (4.22)$$

The filtered array was then processed through the `Resampling.average` reprojection engine. Because the input and output resolutions were both 100 m, the averaging operation primarily acted as a sub-pixel alignment tool, shifting the population values onto the snapped master grid without generating artificial demographic spikes or valleys. The aligned outputs were saved as single-channel demographic grids, guaranteeing spatial coherence with the LULC and NTL datasets.

4.7.3 Precision Vector Masking and the NoData Paradox

While the snapped affine transformation matrix guarantees geometric pixel alignment, the resulting raster matrices initially cover the entire rectangular bounding box encapsulating the target Upazila Group (UG) Zone. For accurate statistical extraction, the analytical data must be strictly confined to the exact vertices of the target GeoJSON or KML vector polygons.

This precise geometric isolation was achieved using the `rasterio.mask` algorithmic library. The masking engine reads the complex vector coordinates of the boundary and burns all raster pixels that fall exterior to the polygon.

A methodological paradox occurs in the treatment of these external burned pixels. If they are assigned an absolute value of zero, subsequent statistical calculations for continuous datasets can produce artificially suppressed means. To resolve this, the pipeline applies a dual-path attribution logic during masking. For optical satellite composites and categorical land-cover datasets, exterior pixels are assigned zero, which renders the exterior padding mathematically null and produces a black background for visualization. Conversely, for demographic and nighttime-light flux datasets, exterior pixels are assigned

NaN. Statistical engines can then ignore these values so that derived means, maximums, and sums represent only the authentic interior geography.

4.7.4 Automated Computational Batch Engine and Hierarchical Distribution

To process the large number of satellite files spanning eight years, five Upazila Group (UG) Zones, twelve economic zones, and the associated spatial configurations, manual operation was structurally unfeasible. An automated computational batch engine was therefore implemented in Python.

The batch engine used dynamic regular-expression (regex) parsing to identify and route datasets. The script scanned input directories and evaluated file nomenclature, matching year identifiers and Upazila Group (UG) Zone tags (for example, `ug1` or `ug5`) so that each source raster could be paired with the appropriate snapped transformation matrix and vector mask.

After resampling and masking, the batch engine hierarchically distributed the resulting 100-m grids into an organized geodatabase. Discrete subdirectories were generated for each economic zone, maintaining separation between zero-offset infrastructure data, 5-km extended-buffer data, and macroscopic Upazila Group data. This file architecture allowed subsequent quantitative extraction, urbanization-index calculation, and visualization scripts to operate systematically.

4.8 Quantitative Data Extraction

Following geospatial harmonization and 100-m master gridding, the continuous and categorical datasets were structurally aligned and stored within localized geodatabases. The subsequent analytical phase translated the spatial pixel arrays into quantifiable tabular demographic and environmental metrics. An automated extraction engine was implemented using Python, Rasterio, and Pandas to minimize manual data-entry errors.

The extraction engine traversed the multi-tiered directory structure, evaluating zero-offset economic zones, 5-km buffer zones, and Upazila Group (UG) Zones. By routing the extraction logic according to raster taxonomy (categorical versus continuous), the algorithm derived absolute areal coverages, statistical flux distributions, and foundational spatial-density indices.

4.8.1 Mathematical Formulation of Categorical Data Extraction (LULC)

The LULC arrays exist as discrete integer matrices representing specific environmental and anthropogenic classes. The objective of the categorical extraction algorithm was to quantify the physical footprint of each land-cover class within the target polygon boundaries.

Let the spatial domain of the target geographic boundary be Ω . The geometrically snapped 100-m master raster covering this domain is represented by a two-dimensional matrix R of dimensions $W \times H$ pixels. Because the geospatial harmonization phase fixed the resolution at 100 m per pixel along both axes, the physical area of a single pixel is:

$$A_{px} = 100 \text{ m} \times 100 \text{ m} = 10,000 \text{ m}^2. \quad (4.23)$$

In square kilometers,

$$A_{px,sqkm} = \frac{10,000}{1,000,000} = 0.01 \text{ km}^2. \quad (4.24)$$

For a land-cover class c , where $c \in \{1 : \text{Farmland}, 2 : \text{Water}, 3 : \text{Forest}, 4 : \text{Built-up}, 5 : \text{Meadow}\}$, an indicator function is defined as:

$$\mathbf{1}_c(x, y) = \begin{cases} 1, & \text{if } R(x, y) = c \\ 0, & \text{if } R(x, y) \neq c. \end{cases} \quad (4.25)$$

A spatial masking function $M(x, y)$ ensures that only pixels inside Ω are evaluated:

$$M(x, y) = \begin{cases} 1, & \text{if pixel at } (x, y) \in \Omega \\ 0, & \text{if pixel at } (x, y) \notin \Omega. \end{cases} \quad (4.26)$$

The total pixel count for class c is:

$$N_c = \sum_{x=1}^W \sum_{y=1}^H (\mathbf{1}_c(x, y) M(x, y)). \quad (4.27)$$

The physical area occupied by class c is:

$$Area_c = N_c \times A_{px,sqkm} = N_c \times 0.01. \quad (4.28)$$

The total valid interior area is:

$$Area_{\text{total}} = \sum_{c=1}^k Area_c, \quad (4.29)$$

where k is the number of recognized land-cover categories. The percentage coverage of class c is:

$$Pct_c = \frac{Area_c}{Area_{\text{total}}} \times 100. \quad (4.30)$$

This evaluation is repeated automatically for every year and every spatial zone, generating the physical footprints of built-up infrastructure, farmland, forest, water, and meadow classes.

4.8.2 Mathematical Formulation of Continuous Flux Extraction (NTL and Population)

Unlike categorical data, NTL radiance and WorldPop demographic datasets operate as continuous, single-channel floating-point matrices. Let $V(x, y)$ represent the physical magnitude at column x and row y . A valid-data mask evaluates whether the pixel belongs to the interior zone and contains a non-negative value:

$$M_{\text{valid}}(x, y) = \begin{cases} 1, & \text{if } (x, y) \in \Omega \text{ and } V(x, y) \geq 0 \\ 0, & \text{otherwise.} \end{cases} \quad (4.31)$$

The number of valid pixels is:

$$N_{\text{valid}} = \sum_{x=1}^W \sum_{y=1}^H M_{\text{valid}}(x, y). \quad (4.32)$$

Four primary statistics are calculated for each continuous matrix. First, the total aggregate sum is:

$$Sum_{total} = \sum_{x=1}^W \sum_{y=1}^H (V(x, y) M_{valid}(x, y)). \quad (4.33)$$

Second, the spatial mean density is:

$$V_{density} = \frac{Sum_{total}}{N_{valid}}. \quad (4.34)$$

Third, the maximum spatial peak is:

$$V_{max} = \max_{(x,y) \in \Omega} (V(x, y) M_{valid}(x, y)). \quad (4.35)$$

Fourth, the spatial variance is calculated as:

$$\sigma^2 = \frac{1}{N_{valid}} \sum_{x=1}^W \sum_{y=1}^H (V(x, y) - \bar{V}_{density})^2 M_{valid}(x, y). \quad (4.36)$$

A high standard deviation indicates concentrated clusters, whereas a lower value indicates a more spatially uniform distribution.

4.8.3 Formulation of Foundational Density Metrics

To synthesize environmental, structural, and demographic extractions into cohesive indicators of industrial development, the extraction engine derives relational density metrics from the independently extracted parameters.

Population density per square kilometer is formulated as:

$$Density_{pop} = \frac{Sum_{POP}}{Area_{total}}, \quad (4.37)$$

where Sum_{POP} is the total aggregate sum of the WorldPop matrix.

Radiance flux density per square kilometer is:

$$Density_{NTL} = \frac{Sum_{NTL}}{Area_{total}}, \quad (4.38)$$

where Sum_{NTL} is the total aggregate sum of the VIIRS NTL matrix.

The built-up infrastructure proportion is:

$$Ratio_{built} = \frac{Area_{built}}{Area_{total}}. \quad (4.39)$$

An increase in $Ratio_{built}$ over 2018–2025 serves as a quantitative proxy for physical industrial expansion.

4.8.4 Data Consolidation and Tabular Formatting

Following iterative execution across all temporal files (2018–2025) and geographic tiers (zero-offset ECZs, 5-km buffers, Upazilas, and Upazila Group (UG) Zones), the resulting numerical outputs were parsed into the Pandas data-manipulation framework.

A comprehensive DataFrame was constructed and grouped by the `Zone_Name` and `Year` attributes. A multidimensional join merged independently extracted LULC areas, NTL

statistics, and population statistics into unified chronological records for each zone and year.

An automated data-cleaning protocol audited the N_{valid} column. Any spatial row reporting exactly zero valid pixels, indicating a non-overlapping geographic anomaly or corrupted boundary geometry, was dropped to prevent zero-division errors in subsequent ratio formulations.

Finally, the DataFrames were chronologically sorted and exported to localized comma-separated-value (CSV) files. The resulting master CSV dataset serves as the quantitative ledger for the research and supplies the statistical evidence required for subsequent urbanization-index calculations and visualization.

4.9 Metric and Index Formulation

After the spatial datasets had been harmonized and the annual zone-level statistics extracted, a multidimensional index framework was constructed to provide comparable measures of development intensity across the twelve Private Economic Zones. The index framework combines categorical LULC proportions with continuous nighttime-light and population density measures. The formulation was designed to distinguish the physical transformation of the land from the broader socioeconomic dimensions of urbanization.

All three reported indices are calculated from the annual observations extracted strictly within the exact zero-offset boundary of each economic zone. The surrounding buffer zones, intersecting Upazilas, and Upazila Group (UG) Zones are not used as the empirical result domains of the indices. They were retained as a reusable spatial framework for future regional and spillover analysis.

4.9.1 Variable Selection Rationale and the Necessity of Spatial Density Metrics

Prior to constructing the composite indices, a methodological decision was required regarding the treatment of the continuous population and nighttime-light variables. The quantitative extraction stage produced both absolute total sums and standardized spatial density measures. For index construction, the absolute sums were not used; instead, Population Density per Square Kilometer (D_{pop}) and Radiance Flux Density per Square Kilometer (D_{ntl}) were selected.

This decision is necessary because the twelve economic zones differ substantially in their physical areas. Absolute population or radiance sums are inherently influenced by the size of the spatial unit. A larger zone can contain a greater total population or cumulative radiance simply because it covers more land, even when its intensity of development is lower than that of a smaller zone. Using absolute sums would therefore introduce area-size bias into a comparative development index.

Density metrics control this effect by expressing the continuous variables relative to the available area. Population density represents the estimated population intensity per square kilometer, while NTL density represents radiance flux relative to the analyzed area. The use of density rather than total accumulation therefore places differently sized economic zones on a more comparable intensity-based basis.

This choice is also consistent with the purpose of the present analysis: the indices are intended to characterize the intensity and trajectory of development within the fixed zero-offset economic-zone footprints rather than simply rank zones according to their physical size.

4.9.2 Base Variable Standardization and Min–Max Normalization

The extracted LULC variables are expressed as percentages bounded between 0 and 100, whereas the continuous population and NTL density variables are measured on different numerical scales. Directly adding these raw quantities would cause variables with larger numerical magnitudes to dominate the resulting index. Therefore, the continuous density variables were transformed to a common $[0, 1]$ scale using Min–Max normalization.

For nighttime-light density, the normalized value is defined as:

$$NTL_{\text{norm}} = \frac{D_{\text{ntl}} - \min(D_{\text{ntl}})}{\max(D_{\text{ntl}}) - \min(D_{\text{ntl}})}. \quad (4.40)$$

Similarly, the normalized population density is defined as:

$$POP_{\text{norm}} = \frac{D_{\text{pop}} - \min(D_{\text{pop}})}{\max(D_{\text{pop}}) - \min(D_{\text{pop}})}. \quad (4.41)$$

For the normalization in Equations (4.40) and (4.41), the minimum and maximum are evaluated over the complete longitudinal observations used for the corresponding analytical spatial tier. For the principal results of this thesis, the relevant observations are the zero-offset economic-zone records. The LULC percentage variables enter the index equations after conversion to the same $[0, 1]$ scale by division by 100.

4.9.3 Normalized Urbanization Index

The first composite measure is the **Normalized Urbanization Index (NUI)**. This index represents the net balance between positive development signals and the loss or displacement of natural and agricultural land-cover components. It combines normalized population density, normalized nighttime-light density, and built-up proportion as positive indicators, while farmland, water, forest, and meadow proportions are treated as opposing components.

The raw form of the index is:

$$U_{\text{raw}} = \left(NTL_{\text{norm}} + POP_{\text{norm}} + \frac{\text{BuiltUp}\%}{100} \right) - \left(\frac{\text{Farmland}\% + \text{Water}\% + \text{Forest}\% + \text{Meadow}\%}{100} \right). \quad (4.42)$$

Because this formulation contains subtractive components, the resulting raw value is not restricted to the interval $[0, 1]$. A second Min–Max transformation is therefore applied to the raw index:

$$NUI = U_{\text{norm}} = \frac{U_{\text{raw}} - \min(U_{\text{raw}})}{\max(U_{\text{raw}}) - \min(U_{\text{raw}})}. \quad (4.43)$$

The final NUI is therefore expressed on a $[0, 1]$ scale within the observed analytical dataset. Lower values represent relatively less urbanized states and higher values represent relatively more urbanized states within the comparative longitudinal framework.

4.9.4 Equally Weighted Core Urbanization Index

The second measure is the **Equally Weighted Core Urbanization Index (ECUI)**. This index was formulated to isolate the three principal positive dimensions of anthropogenic development: physical built-up infrastructure, nighttime economic activity, and human

settlement. Unlike the NUI, the ECUI does not subtract natural or agricultural land-cover classes. This avoids allowing large quantities of water, forest, farmland, or meadow within a zone to conceal positive evidence of physical or socioeconomic development.

Each of the three components receives an equal weight of one-third. The index is defined as:

$$ECUI = I_{\text{tri}} = \frac{1}{3}POP_{\text{norm}} + \frac{1}{3}NTL_{\text{norm}} + \frac{1}{3}\left(\frac{BuiltUp\%}{100}\right). \quad (4.44)$$

Because each component is bounded between 0 and 1 and the three components are equally weighted, the resulting ECUI is also bounded within the interval $[0, 1]$. The index consequently provides a positive, equally weighted measure of core anthropogenic development intensity.

4.9.5 Normalized LULC Dynamics Index

The third measure is the **Normalized LULC Dynamics Index (NLDI)**. This index is designed to represent the physical land-transformation dimension independently of population density and nighttime-light intensity. It therefore uses only the five reported LULC proportions.

The raw physical transformation measure is:

$$LULC_{\text{raw}} = \frac{BuiltUp\% - Meadow\% - Forest\% - Water\% - Farmland\%}{100}. \quad (4.45)$$

The resulting raw value can be positive or negative depending on the balance between built-up land and the combined remaining LULC classes. To place the measure on a standardized scale for longitudinal comparison, a final Min–Max normalization is applied:

$$NLDI = LULC_{\text{norm}} = \frac{LULC_{\text{raw}} - \min(LULC_{\text{raw}})}{\max(LULC_{\text{raw}}) - \min(LULC_{\text{raw}})}. \quad (4.46)$$

The NLDI therefore isolates the physical land-cover dimension of development and provides a complementary trajectory against which the multidimensional NUI and ECUI can be interpreted.

4.9.6 Relationship Among the Three Indices

The three indices are intentionally complementary rather than interchangeable. The NUI combines positive development signals with an explicit penalty for the remaining agricultural and natural land-cover proportions. The ECUI focuses only on the three positive anthropogenic dimensions and assigns them equal weight. The NLDI isolates physical land transformation using LULC alone.

Accordingly, differences among the three trajectories are analytically meaningful. For example, a zone may show increasing built-up land and therefore an increasing NLDI while exhibiting a slower change in ECUI if population density or nighttime-light density changes more gradually. Conversely, a zone with a high development baseline may have a strong ECUI but a smaller NUI change if substantial agricultural or natural land remains within its fixed footprint. The comparison of the three indices is therefore used in the Results and Discussion chapters to distinguish physical transformation from broader socioeconomic development intensity.

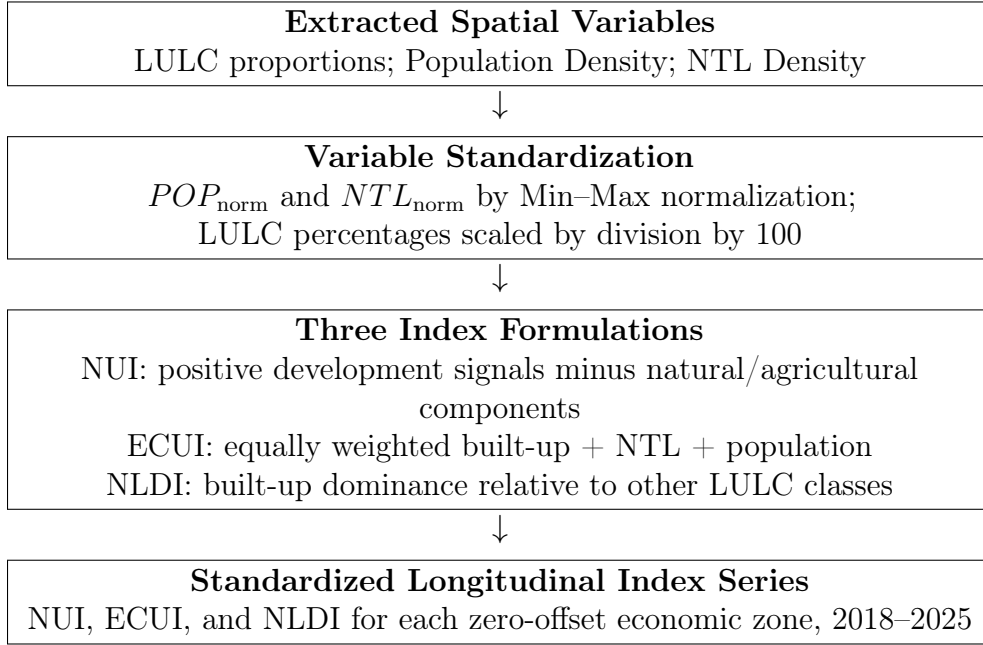


Figure 18: Mathematical architecture of the three multidimensional development indices constructed from the extracted LULC, nighttime-light, and population variables.

Figure 18 summarizes the relationship between the extracted variables, their standardization, and the three final index formulations. The figure is intended as a methodological overview; the individual equations define the numerical implementation used in the analysis.

4.10 Spatiotemporal Assessment

The final analytical stage evaluates the annual evolution of the twelve zero-offset economic zones over the common 2018–2025 observation window. The extracted LULC composition, NTL density, population density, and composite indices are compared year by year and between the study-period endpoints. Annual trajectories are used to identify gradual growth, abrupt transitions, temporary fluctuations, and relatively stable development patterns.

The spatial analysis is conducted at the level of the individual economic-zone polygons. The four trajectory groups reported in the Results and Discussion chapters are used as comparative groupings of zones with similar longitudinal behavior across the study period. These analytical groupings should not be confused with the five Upazila Group (UG) Zones used as spatial supersets for data acquisition and processing. The UG Zones and the four analytical trajectory groupings serve different purposes.

The spatiotemporal assessment compares both absolute levels and changes over time, including changes in LULC composition, NTL density, population density, and the three composite indices. Cluster-level summaries, endpoint comparisons, trajectory ranges, and deviations from linear endpoint-based growth patterns are then used to interpret the different development pathways observed among the economic zones.

5. Experimental Setup

This chapter documents the fixed analytical configuration under which the methods described in Chapter 4 were executed. It does not introduce a separate analytical method or redefine the study area. Instead, it establishes the experimental organization, fixed spatial and temporal settings, evaluation and validation criteria, and the visual checks used to confirm that the processed data products were suitable for the subsequent longitudinal analysis. The reported quantitative analysis remains restricted to the exact zero-offset boundaries of the twelve selected Private Economic Zones.

5.1 Experimental Framework

The longitudinal experiment was organized around twelve selected Private Economic Zones observed over eight annual time points from 2018 through 2025. The exact zero-offset polygon of each economic zone was maintained as the primary analytical boundary throughout the reported analysis. For each annual observation, three principal analytical data streams were available: land use and land cover (LULC), nighttime-light (NTL) radiance, and gridded population.

The LULC data were produced from the Gamma S2DR4-derived 2-m optical imagery and subsequently represented on the common 100-m grid. The NTL and population datasets were likewise represented on the same spatial framework, allowing corresponding cells to be compared across data sources. The common spatial framework therefore establishes a consistent basis for extracting annual zone-level quantities and constructing the three development indices defined in Chapter 4. The overall experimental organization of the longitudinal analysis is presented in Figure 19 as:

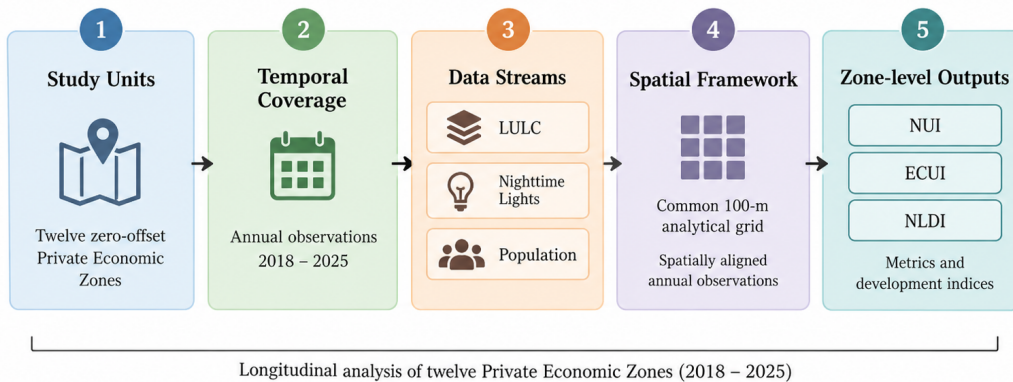


Figure 19: Experimental organization used for the longitudinal analysis of the twelve Private Economic Zones.

Figure 19 summarizes the experimental structure without introducing an additional processing stage. The detailed acquisition, preprocessing, harmonization, extraction, and index-construction procedures are provided in Chapter 4.

The surrounding 1–5 km buffers, intersecting Upazila geometries, and five Upazila Group (UG) Zones were not treated as additional result populations in the present experiment. They served as supporting spatial infrastructure and acquisition supersets and were retained for future regional and spillover investigations. Their prepared spatial extents were also used in selected visual validation examples so that the broader applicability of the processing workflow could be inspected without changing the primary analytical domain.

5.2 Experimental Settings

The following settings were held consistently across the longitudinal experiment.

Table 9: Fixed experimental settings used for the longitudinal spatial analysis.

Parameter	Experimental setting
Primary spatial units	Twelve exact zero-offset Private Economic Zone boundaries
Temporal window	2018–2025, organized as annual observations
Contextual spatial extent	5-km contextual extent around the economic zones for visual inspection and supporting spatial preparation
Common analytical grid	100 m $\times$ 100 m
Coordinate reference system for processing	EPSG:3857
Optical analytical product	2-m RGB imagery generated through the Gamma S2DR4 workflow from Sentinel-2 observations
LULC representation	Five analytical classes: Farmland, Water, Forest, Built-up, and Meadow
LULC-to-100-m aggregation	Majority-rule (modal) class assignment
NTL source	VIIRS VNP46A3 radiance data
NTL-to-100-m transformation	Continuous-value area-weighted averaging
Population source	WorldPop 100-m gridded population
Population treatment	Alignment to the common 100-m master grid without changing the source population meaning
Continuous-variable standardization	Min–Max normalization for Population Density and NTL Density before composite index construction
Development indices	Normalized Urbanization Index (NUI), Equally Weighted Core Urbanization Index (ECUI), and Normalized LULC Dynamics Index (NLDI)

These settings define the common experimental environment without repeating the acquisition and processing algorithms already described in Chapter 4. The mathematical definitions of the three indices are likewise retained in Chapter 4.

5.3 Evaluation and Validation Criteria

Because the research combines heterogeneous geospatial datasets rather than evaluating a single predictive model against a conventional benchmark, validation was performed at the data-product and spatial-consistency levels.

5.3.1 Spatial Boundary Consistency

All annual quantitative measurements were extracted using the same zero-offset polygon definition for each economic zone. The boundary therefore remains fixed through the longitudinal series, preventing changes in the geometry of the analytical unit from being interpreted as temporal land-cover or development change.

5.3.2 Cross-Source Spatial Alignment

The LULC, NTL, and population datasets were required to occupy the same 100-m cell footprints after harmonization. This alignment is essential because the composite development measures combine variables originating at different native spatial resolutions. A cell in one data layer must correspond to the same physical ground footprint in the other layers before cell-level comparison or aggregated zone-level extraction is interpreted.

5.3.3 LULC Visual Plausibility

The inferred LULC maps were visually inspected against the corresponding high-resolution optical imagery. Particular attention was given to built-up structures, roads and industrial surfaces, agricultural parcels, water bodies, and vegetated areas. The purpose of this check was not to replace formal model evaluation, but to identify obvious spatial inconsistencies, artifacts, or implausible class assignments in the processed outputs.

5.3.4 Numerical Validity and NoData Handling

The continuous NTL and population products were inspected to ensure that negative fill values and exterior NoData regions did not contribute to the quantitative statistics. The same masking logic used during the processing stage was maintained during extraction so that sums, means, and density measures represented only valid pixels within the intended geographic boundary.

5.3.5 Temporal Consistency

The annual analysis was conducted using the same spatial definitions, data-processing logic, 100-m analytical framework, extraction rules, and index formulations throughout 2018–2025. This consistency was necessary to make the observed longitudinal trajectories comparable across years and across the twelve economic zones.

5.4 Spatial and Data-Product Validation

The visual validation stage was designed to provide a direct inspection of the intermediate spatial products generated by the processing workflow. The validation uses a **5-km contextual extent** around representative economic zones. This extent is used only to provide geographic context and to demonstrate that the processed products can be

inspected together across a broader landscape; the reported longitudinal statistics and development indices remain based on the exact zero-offset economic-zone boundaries.

5.4.1 Buffered Spatial Visualization and Intermediate-Product Inspection

For representative validation cases, the continuous super-resolved optical mosaic was cropped to the 5-km contextual extent surrounding the economic zone and inspected together with the corresponding LULC classification. This comparison permits visual checking of whether the high-resolution optical product preserves recognizable spatial features and whether the LULC output follows visually identifiable patterns.

For the Meghna Economic Zone, the representative 2018 optical RGB composite is shown in Figure 20. The image presents the optical RGB composite produced through the Sentinel-2 and Gamma S2DR4 workflow within the 5-km contextual extent.

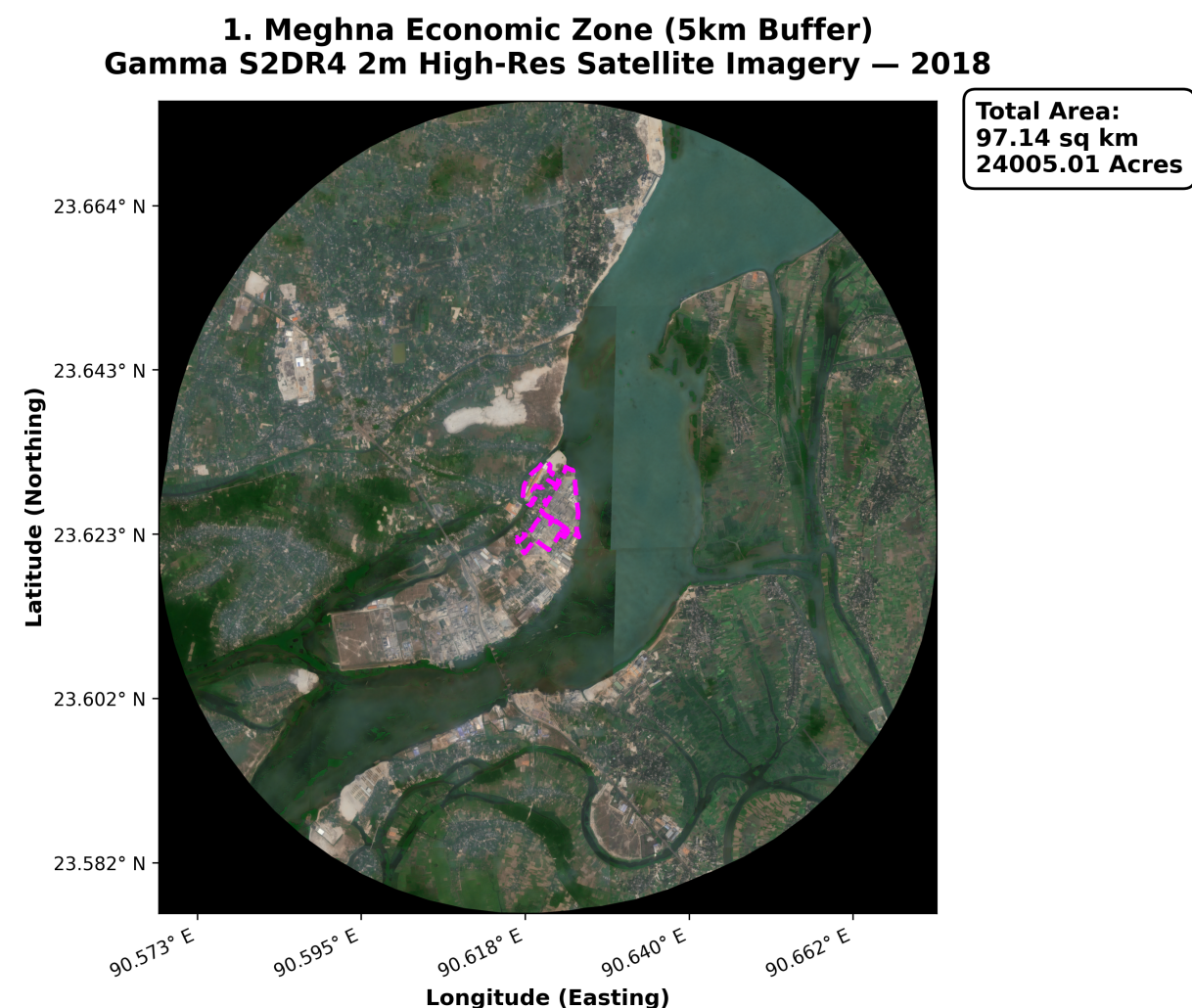


Figure 20: Optical RGB composite for Meghna Economic Zone in 2018 within the 5-km contextual extent, produced from Sentinel-2 imagery and super-resolved to 2m using the Gamma S2DR4 workflow.

The corresponding five-class LULC classification for the same buffered extent is shown separately in Figure 21. The classification was produced by the adapted classification workflow and represents the five analytical classes used throughout this study.

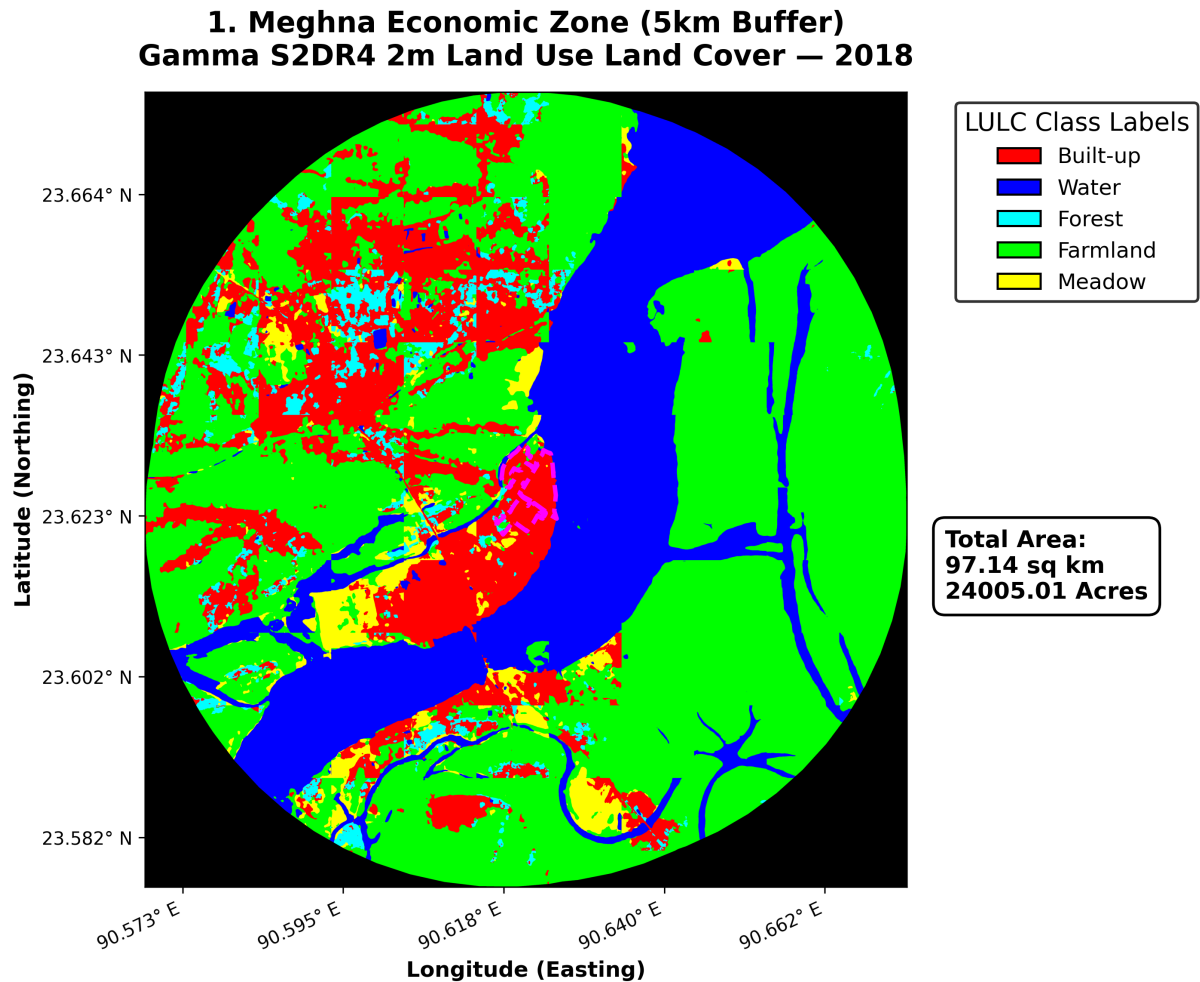


Figure 21: Five-class LULC classification for Meghna Economic Zone in 2018 within the same 5-km contextual extent. The classification comprises Built-up, Farmland, Water, Forest, and Meadow classes.

The comparison between Figures 20 and 21 is interpreted as an intermediate-product validation: built-up areas, agricultural land, water, forest, and meadow classes should correspond spatially to recognizable features in the underlying optical imagery. The same visual checking principle was applied across the selected zones and representative years.

5.4.2 Common 100-m Grid Alignment Verification

The second validation stage verifies that the three analytical data layers share a common 100-m spatial footprint. The 2-m LULC classification is represented at 100 m using the majority-rule class, the approximately 462-m NTL observations are represented at 100 m through continuous area-weighted averaging, and the 100-m population data are aligned to the same master grid.

The resulting grid correspondence is examined visually using the Meghna Economic Zone as a representative case. The cell boundaries are displayed to make the common spatial framework explicit. Figure 17 represents the Meghna Economic Zone Level 100m-Gridding. Figure 22 illustrates the conversion of the 2-m categorical LULC classification to the common 100-m master grid for its extended 5km buffer zone, while Figures 23 and 24 show the corresponding NTL and population representations on the same spatial framework.

The three aligned layers can therefore be visually inspected as a common spatial matrix.

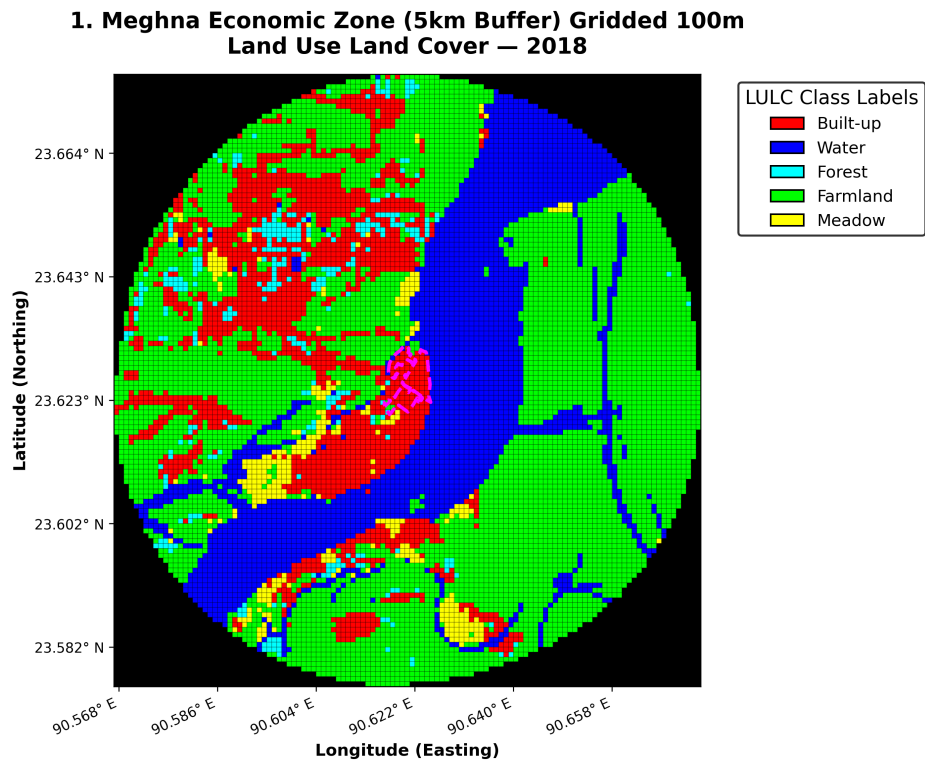


Figure 22: Illustrative conversion of the 2-m categorical LULC classification to the common 100-m master grid using majority-rule aggregation.

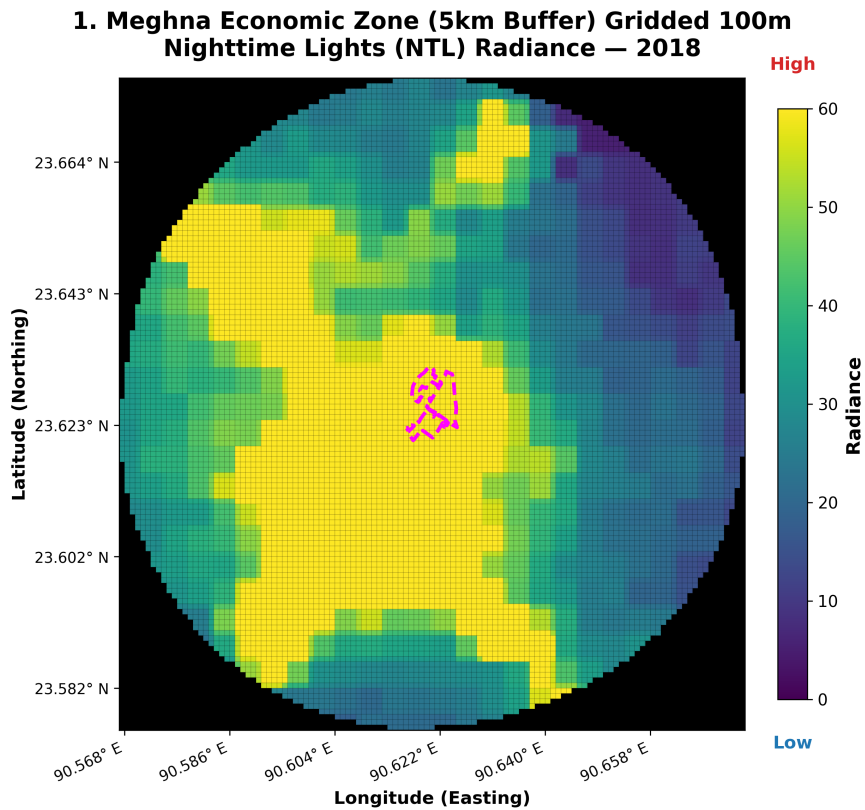


Figure 23: Night-Time Lights radiance represented on the common 100-m grid for Meghna Economic Zone within the 5-km contextual extent, 2018.

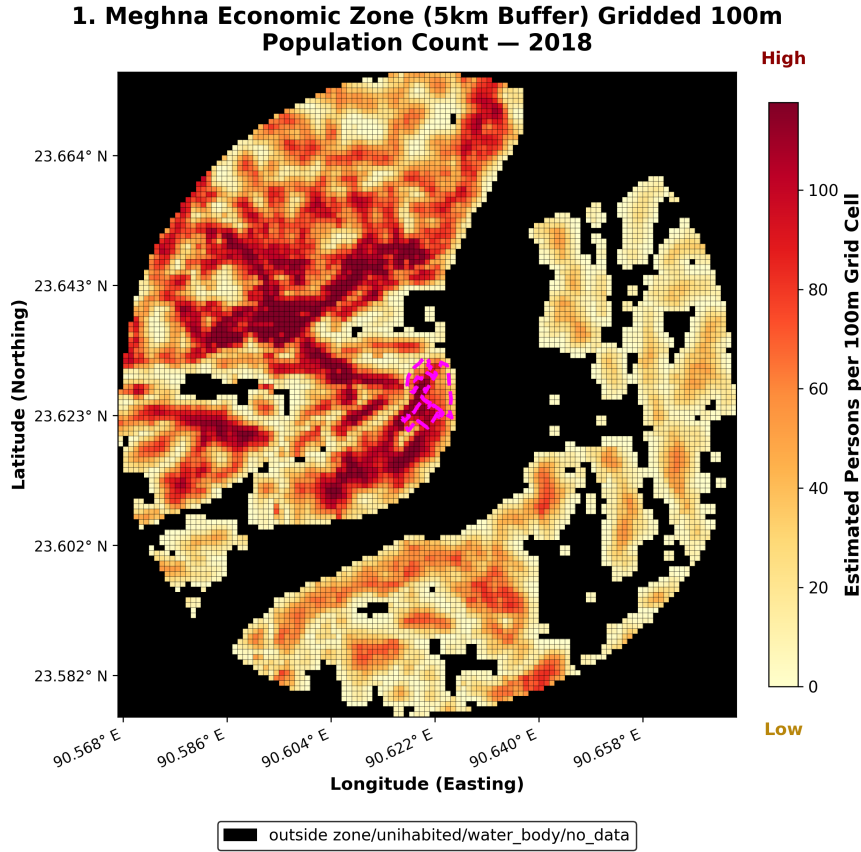


Figure 24: Population surface represented on the common 100-m grid for Meghna Economic Zone within the 5-km contextual extent, 2018.

A particular 100-m cell in the LULC layer corresponds to the same geographic footprint as the associated NTL and population cells. This alignment is the spatial prerequisite for combining the variables in the subsequent zone-level extraction and index construction.

5.4.3 Integrated Zone-Level Multi-Source Comparison

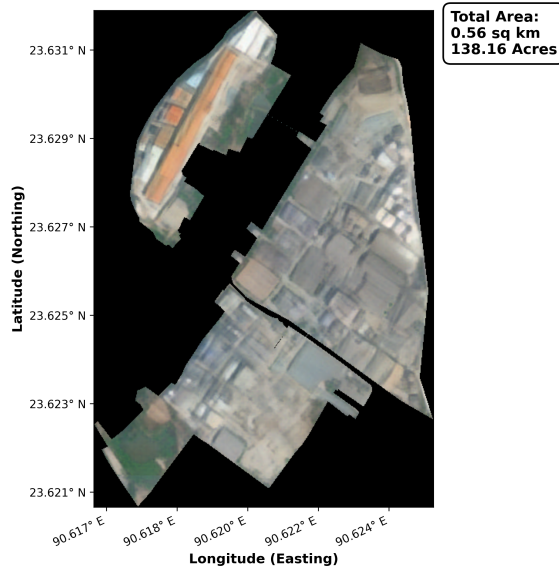
The final visual validation stage combines the optical imagery, LULC, NTL, and population products for a representative economic zone. The same spatial extent and panel arrangement are used for two years so that the progression of physical, luminous, and demographic signals can be inspected together.

For the representative Meghna Economic Zone, the 2018 multi-source configuration is shown in Figure 25. The corresponding 2025 configuration is shown in Figure 26. In each case, the four panels provide a consistent visual arrangement of the optical imagery, 100-m LULC, 100-m NTL, and 100-m population products within the same 5-km contextual extent.

The corresponding 2025 configuration uses the same spatial extent and panel arrangement, as shown in Figure 26.

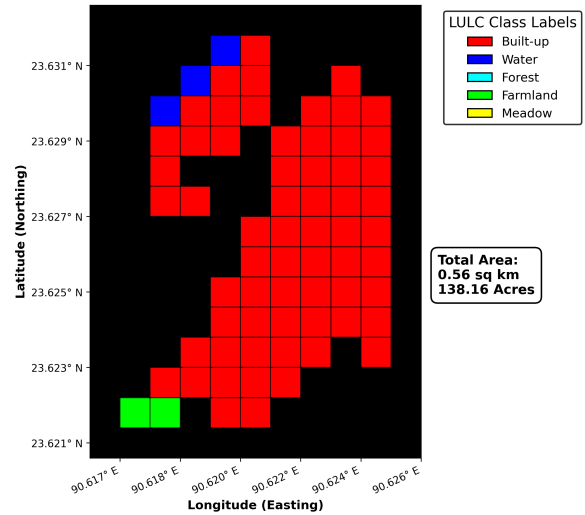
The 2018 and 2025 panels provide a qualitative year-to-year check of the spatial correspondence among the data streams and illustrate how the same analytical framework can be used to inspect temporal change. The figures are not treated as substitutes for the quantitative results presented in Chapter 6.

**1. Meghna Economic Zone
Gamma S2DR4 2m High-Res Satellite Imagery — 2018**



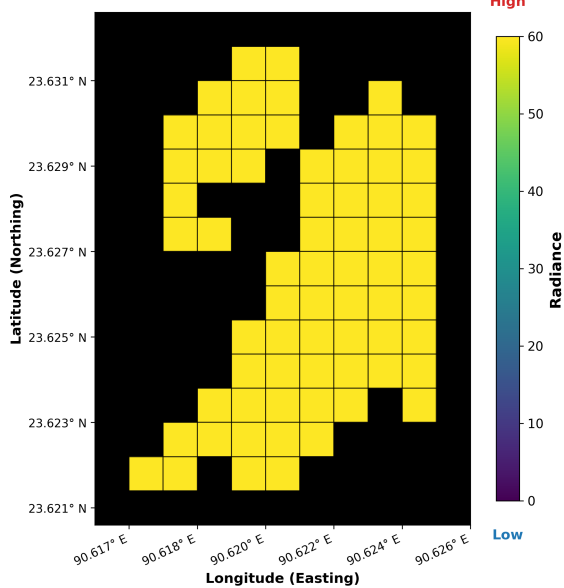
(a) Native satellite composite

**1. Meghna Economic Zone Gridded 100m
Land Use Land Cover — 2018**



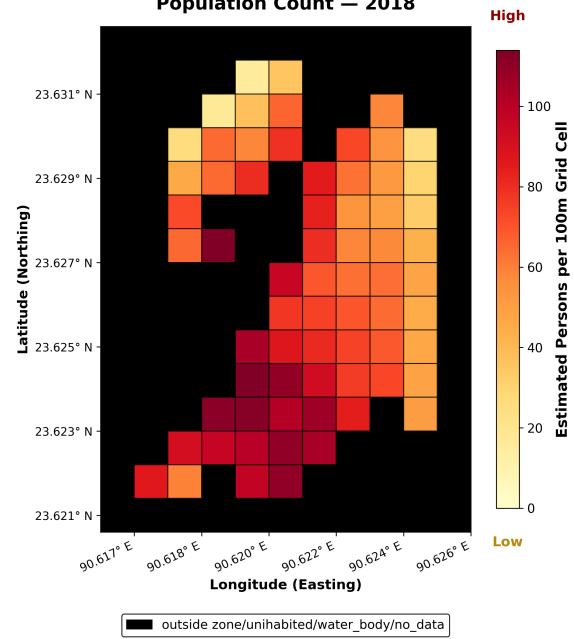
(b) LULC grid (100 m)

**1. Meghna Economic Zone Gridded 100m
Nighttime Lights (NTL) Radiance — 2018**



(c) Night-Time Lights grid (100 m)

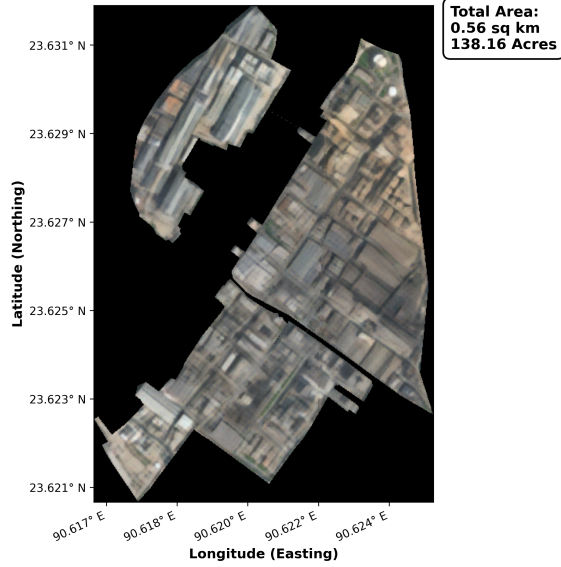
**1. Meghna Economic Zone Gridded 100m
Population Count — 2018**



(d) Population density grid (100 m)

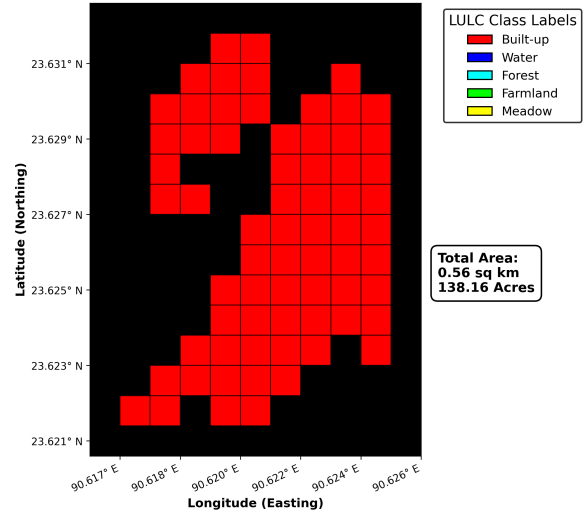
Figure 25: Integrated multi-source spatial comparison for (1) Meghna Economic Zone, 2018, within its 5,000 m buffer, comprising (a) native satellite imagery, (b) 100-m LULC, (c) 100-m Night-Time Lights, and (d) 100-m population density.

**1. Meghna Economic Zone
Gamma S2DR4 2m High-Res Satellite Imagery — 2025**



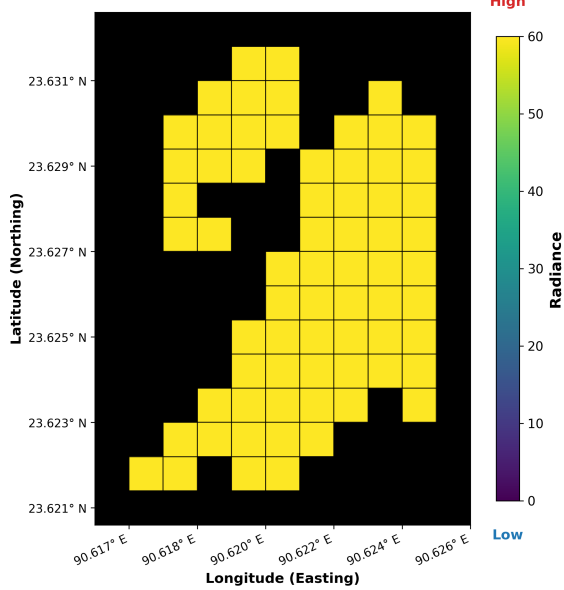
(a) Native satellite composite

**1. Meghna Economic Zone Gridded 100m
Land Use Land Cover — 2025**



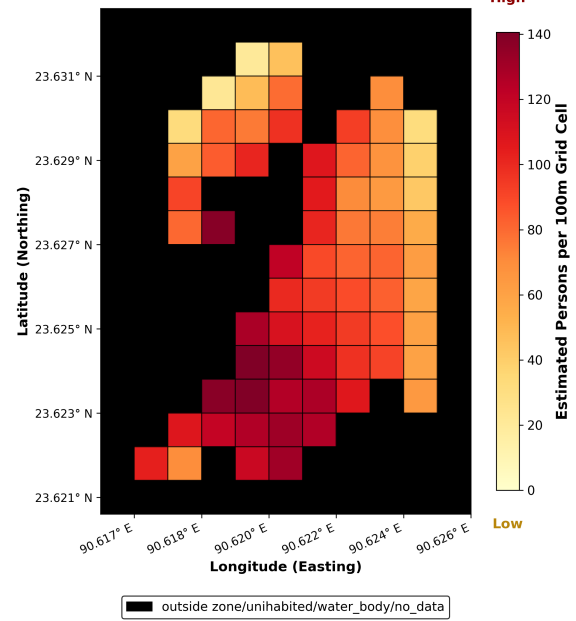
(b) LULC grid (100 m)

**1. Meghna Economic Zone Gridded 100m
Nighttime Lights (NTL) Radiance — 2025**



(c) Night-Time Lights grid (100 m)

**1. Meghna Economic Zone Gridded 100m
Population Count — 2025**



(d) Population density grid (100 m)

Figure 26: Integrated multi-source spatial comparison for (1) Meghna Economic Zone, 2025, within its 5,000 m buffer, comprising (a) native satellite imagery, (b) 100-m LULC, (c) 100-m Night-Time Lights, and (d) 100-m population density.

5.4.4 Cartographic Visualization

Categorical LULC outputs were visualized using the predefined class representation, while continuous NTL and population surfaces were displayed using consistent radiometric or density scaling so that the spatial patterns could be inspected without allowing isolated extreme values to dominate the visual range. Where 100-m grid visualization was required, cell boundaries were generated from the common affine transform established in Chapter 4.

5.4.5 Longitudinal Trend Visualization

Annual values from 2018 to 2025 were plotted for each zone to show the temporal evolution of LULC composition, NTL density, population density, and the three derived development indices. Endpoint comparisons between 2018 and 2025 were used where appropriate to summarize net changes, while the full annual series were retained to reveal intermediate peaks, plateaus, reversals, and divergent trajectories.

The resulting plots and tables are presented and interpreted in Chapter 6. This chapter therefore documents the experimental configuration and validation basis rather than duplicating the numerical findings.

6. Results and Discussion

The spatial extent of LULC within the zero-offset boundaries of the twelve Private Economic Zones for 2018, 2019, 2023, and 2025 is presented in the corresponding figures, showing differing magnitudes and trajectories of land-cover change across the study zones. For each zone, annual pixel counts and percentages were computed for the five LULC classes, Farmland, Water, Forest, Built-up, and Meadow, together with annual NTL density and population density. These zone-level measures form the empirical basis for the three development indices defined in Chapter 4 and evaluated below. Because the same spatial units are compared across all twelve zones and throughout 2018–2025, the index analysis is *inter-zone* in the comparative sense, while the underlying measurements remain restricted to the exact zero-offset footprint of each individual economic zone.

For the standardized index series discussed below, scores are presented on a common 0–1 scale. Higher values indicate greater relative development intensity or physical build-out within the observed zone-year dataset; a value of 0 does not represent zero development in an absolute real-world sense, and a value of 1 does not represent a universal maximum. Instead, the standardized scores express the relative position of each observed zone-year within the corresponding index framework. The three indices emphasize different dimensions of development: the Normalized Urbanization Index (NUI) combines built-up, NTL, and population signals while accounting for the remaining LULC components, the Equally Weighted Core Urbanization Index (ECUI) combines the three positive anthropogenic signals with equal weighting, and the Normalized LULC Dynamics Index (NLDI) isolates the physical land-cover transformation dimension. Their trajectories are subsequently compared using the four observed development clusters identified from the longitudinal patterns with $k = 4$ K-Means clustering.

6.1 Land Use Land Cover Parameters (Pixel Counts)

The annual pixel-count trends for the five LULC classes (farmland, water, forest, built-up, and meadow) across the twelve private economic zones (2018–2025) reveal a consistent typology: zones already embedded in the Dhaka-Narayanganj urban core undergo rapid consolidation into built-up land at the expense of all other classes, coastal and riverine zones are structurally constrained by their site geometry regardless of urbanization pressure, and several agrarian zones show a direct, near-mechanical trade-off between farmland loss and meadow gain rather than farmland converting straight to built-up land. A further group of zones shows neither conversion pathway, remaining essentially stable across the full study period. These patterns are examined below in four parts: built-up expansion and urban consolidation; farmland, meadow, and the agrarian and dual-source displacement pathways; water and forest dynamics; and a closing synthesis of the distinct land-cover change pathways identified across the twelve zones.

6.1.1 Built-up Expansion and Urban Consolidation

Figures 27 and 28 show the changes in land-use and land-cover classes across the economic zones from 2018 to 2025. In particular, they highlight the relationship between the expansion of built-up areas and the corresponding reduction in natural and agricultural land-cover classes.

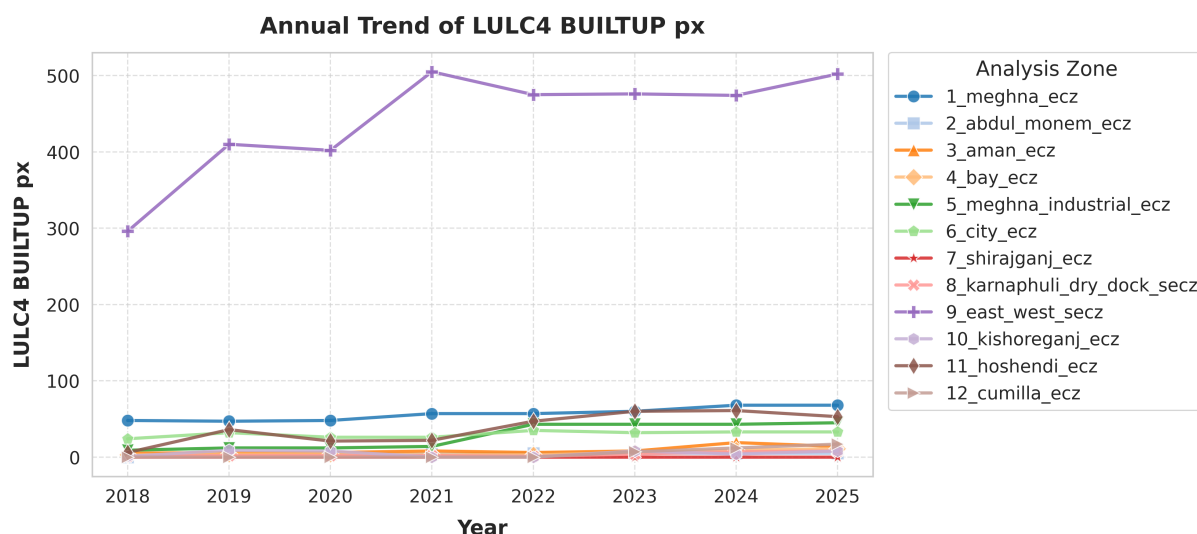


Figure 27: Annual trend of LULC4 Built-up pixel count (2018–2025) across the twelve economic zones.

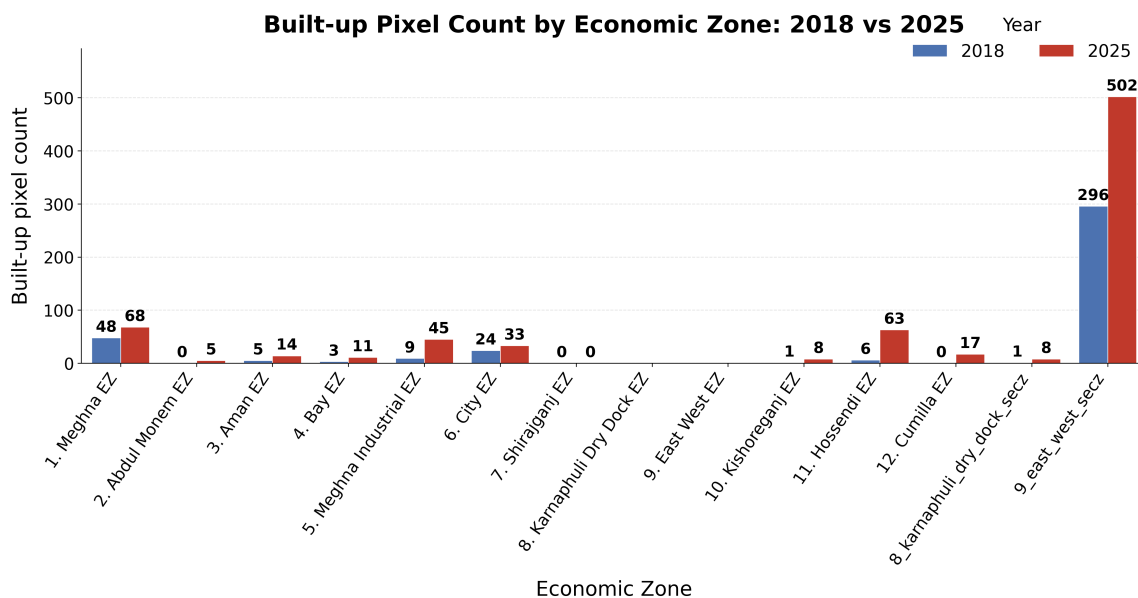


Figure 28: Built-up (LULC-4) pixel count by economic zone, 2018 vs 2025.

The clearest built-up expansion is seen in (9) East West Special Economic Zone, which recorded the highest built-up pixel count of any zone by 2025 (500 px), a drastic increase from its 2018 baseline. This expansion mirrors matching collapses in the zone's other classes: its forest cover, the highest among all zones in 2018 (more than 14 px), fell to 0 px by 2021 and remained there; its meadow cover likewise fell drastically from 2018 to 2021 and stayed near 0 px through 2025; and its water body, the largest of any zone in 2018 (more than 55 px), dropped sharply from 2018 to 2022 before only a slow partial recovery through 2025. Together these four trends describe a single process, near-total

conversion of (9) East West Special Economic Zone’s land cover into built-up area over the study period.

A comparable but more gradual pattern appears in (1) Meghna Economic Zone, whose built-up pixel count rose steadily from roughly 50 px to 70 px between 2018 and 2025, consistent with its already-low farmland presence as an urban-area zone. (5) Meghna Industrial Economic Zone’s built-up count rose to roughly 30 px, accompanied by a gradual decline in its meadow cover across 2018–2025 and a brief rise in forest cover to about 10 px in 2020–2021 before settling back to 7 px, indicating more mixed, non-linear land-cover turnover rather than a single dominant conversion pathway. By contrast, (6) City Economic Zone’s built-up count remained somewhat volatile across the full period, at 24 px in 2018 and 33 px in 2025, and all remaining zones stayed below 20 px in built-up pixel count with only minimal year-to-year change, indicating negligible construction activity over 2018–2025.

6.1.2 Farmland and Meadow: Agrarian Conversion and Dual-Source Displacement

The following Figures 29–32 highlight another important land-cover transition observed across the economic zones. Unlike the previous pattern, where farmland was primarily converted into built-up areas, these figures demonstrate a clear relationship between the reduction of farmland and the simultaneous expansion of meadow cover.

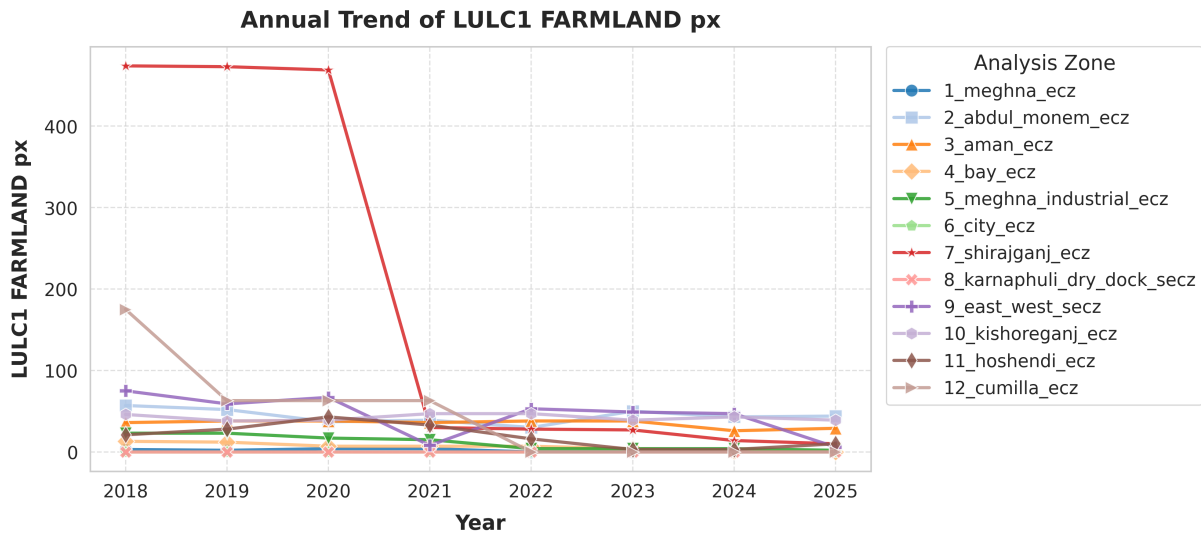


Figure 29: Annual trend of LULC1 Farmland pixel count (2018–2025) across the twelve economic zones.

A direct farmland to meadow conversion is visible in the two zones with the largest raw land areas under cultivation. (7) Shirajganj Economic Zone held the highest farmland pixel count of any zone from 2018 to 2020 (more than 460 px), which collapsed sharply in 2021 as a direct consequence of a corresponding rise in meadow cover. From 2021 onward, (7) Shirajganj Economic Zone instead recorded the highest meadow pixel count of any zone (more than 450–460 px), while its residual farmland continued to decline slowly through 2025.

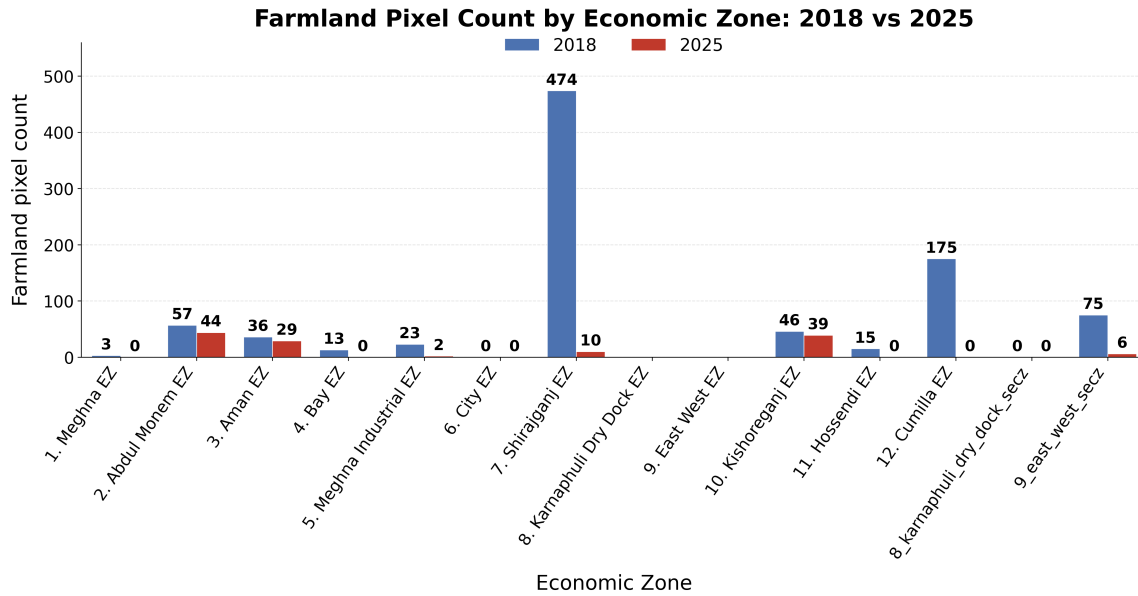


Figure 30: Farmland (LULC1) pixel count by economic zone, 2018–2025.

The 2018-versus-2025 comparison in Figure 30 makes the scale of this farmland loss explicit: (7) Shirajganj Economic Zone and (12) Cumilla Economic Zone show among the largest bar-height reductions of any class in this study, both falling from several hundred pixels of farmland in 2018 to near-zero by 2025. Zones already embedded in the urban core, together with (8) Karnaphuli Dry Dock Special Economic Zone’s site-geometry-driven absence of farmland, appear as uniformly low bars in both years, visually confirming that their minimal farmland reflects a baseline condition rather than a 2018–2025 conversion.

(12) Cumilla Economic Zone shows the same underlying dynamic on a smaller scale, farmland peaked in 2018 (more than 160 px), fell to roughly 70 px by 2019–2021, and was reduced to near 0 px from 2022 onward, while meadow pixel count rose over the same interval, increasing sharply in 2019 to 119 px, holding roughly constant through 2021, and reaching its highest value of the series in 2022 (more than 170 px) before declining slightly to 165 px by 2025. In both zones, farmland loss and meadow gain move in near lock-step, distinguishing this conversion pathway from the farmland-to-built-up pathway described in Section 6.1.1.

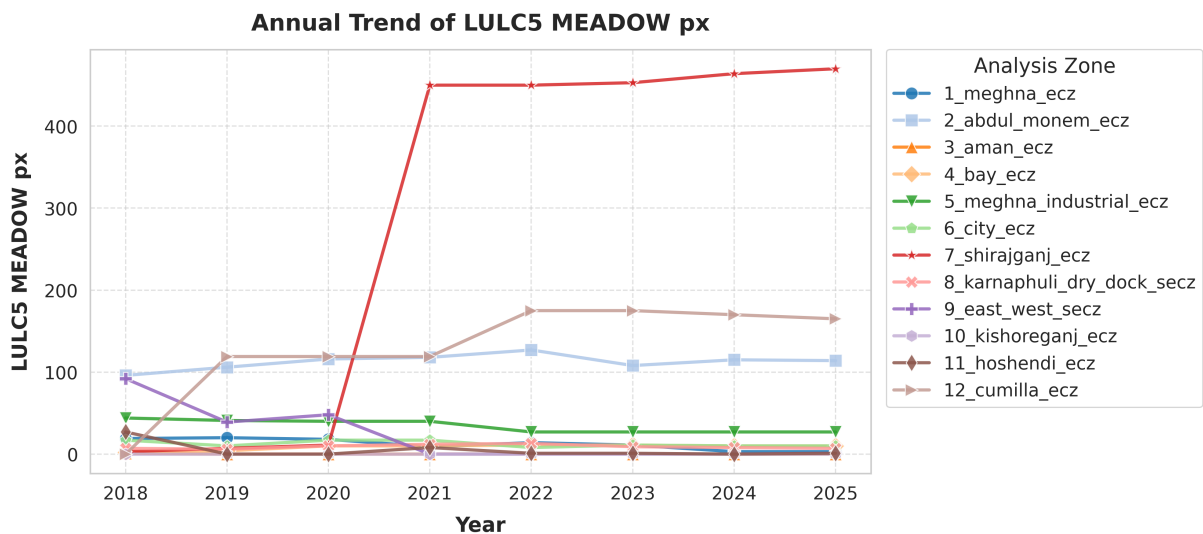


Figure 31: Annual trend of LULC5 Meadow pixel count (2018–2025) across the twelve economic zones.

(11) Hossaindi Economic Zone illustrates a third, distinct pathway in which both farmland and meadow are displaced directly by built-up expansion, rather than converting into one another. Its farmland pixel count held steady at 14–15 px from 2018 through 2021, then declined sharply to 5 px in 2022, 1 px in 2023, and 0 px from 2024 onward. Its meadow pixel count followed a more variable but ultimately similar decline, falling from 33 px in 2018 to 14 px in 2019, recovering to 29 px in 2020 and 27 px in 2021, and then declining steadily to 12 px in 2022, 3 px in 2023–2024, and 1 px by 2025. Both classes collapse over 2021–2025, the same window in which (11) Hossaindi Economic Zone’s built-up pixel count climbs from 22 px to 63 px (Figure 27), indicating that construction activity in this zone drew directly on both farmland and meadow rather than following the single-source conversion pattern seen in (7) Shirajganj Economic Zone and (12) Cumilla Economic Zone.

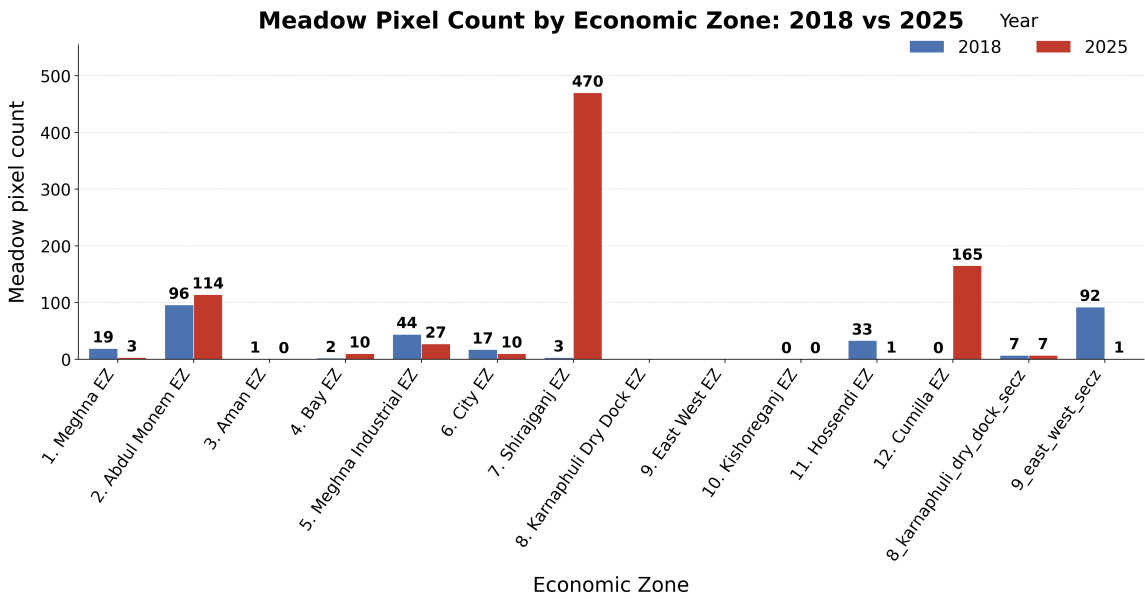


Figure 32: Meadow (LULC5) pixel count by economic zone, 2018 vs 2025.

Figure 32 isolates the net meadow change at the two study endpoints. (7) Shirajganj Economic Zone and (12) Cumilla Economic Zone show the largest 2018-to-2025 gains in the dataset, consistent with the farmland-to-meadow conversion described above, while (11) Hossaindi Economic Zone’s bars decline modestly between the two years despite the more volatile intra-period path shown in Figure 31. The remaining zones show comparably low bars in both years, reflecting the broader pattern in which meadow change outside the two agrarian-conversion zones is minor relative to the farmland and built-up shifts described above.

Several zones instead show land-cover stability rather than conversion. (2) Abdul Monem Economic Zone, (10) Kishoreganj Economic Zone, and (3) Aman Economic Zone all maintained roughly constant farmland pixel counts across 2018–2025, with no major change recorded over the study period; (3) Aman Economic Zone’s meadow cover was similarly stable across the same window (Figures 29 and 31). This stability contrasts with the urban-core zones described in Section 6.1.1 and suggests these three zones experienced comparatively little land-cover pressure from either urbanization or agricultural transition during 2018–2025.

Site geometry imposes a further structural constraint on the farmland class, independent of urbanization pressure. (8) Karnaphuli Dry Dock Special Economic Zone, located directly on the shoreline, records no farmland pixels at any point in the series (Figure 30). (4) Bay Economic Zone, (1) Meghna Economic Zone, (5) Meghna Industrial Economic Zone, and

(6) City Economic Zone, all situated within the urban area, likewise show significantly lower farmland pixel counts, ranging to none, across the full 2018–2025 period, a baseline condition rather than a trend, distinguishing these zones from those undergoing active farmland conversion.

6.1.3 Water and Forest Dynamics

Water and forest are the two smallest LULC classes by areal extent across the twelve economic zones, together typically accounting for a small minority of any zone’s total footprint. Unlike farmland, meadow, and built-up land, which show sustained, multi-year directional trends and, in several zones, direct conversion between one another, water and forest pixel counts are largely static and zone-specific, driven by fixed site characteristics (proximity to a riverbank, presence of a shoreline) rather than by the gradual urbanization processes described in the preceding subsections. The two exceptions to this general stability, (9) East West Special Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone, are each linked to a distinct and identifiable physical driver rather than to ongoing land-use conversion, as detailed below.

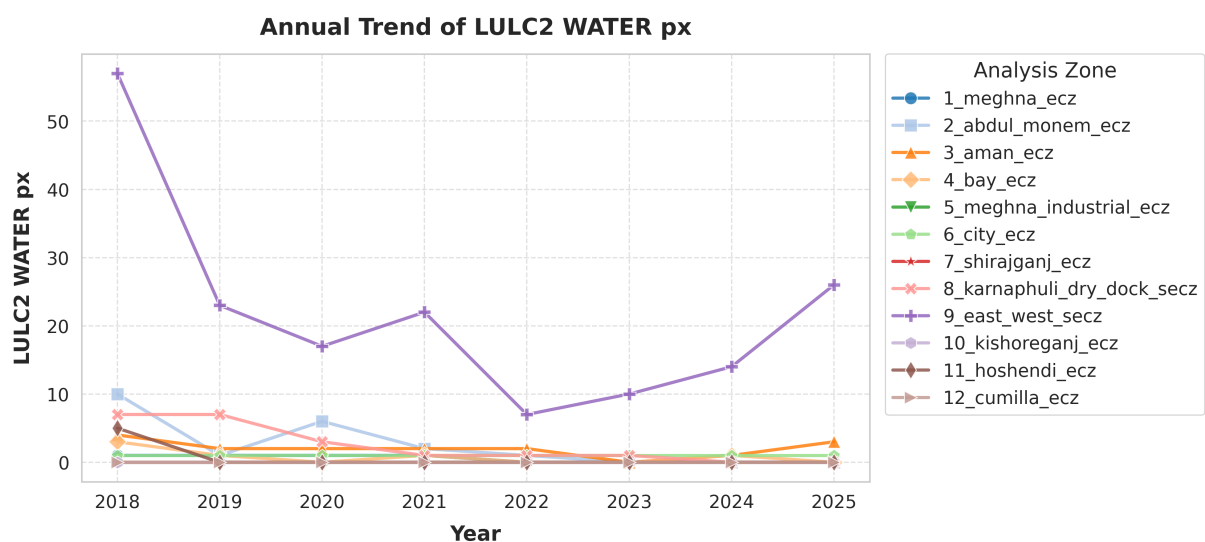


Figure 33: Annual trend of LULC2 Water pixel count (2018–2025) across the twelve economic zones.

Figure 33 shows that water pixel counts remain minimal across nearly all twelve zones throughout 2018–2025, with two clear exceptions. (9) East West Special Economic Zone recorded the highest water pixel count of any zone in 2018 (more than 55 px), as discussed in relation to its built-up expansion in Section 6.1.1; this water body declined sharply through 2022 before a slow, partial recovery through 2025. (8) Karnaphuli Dry Dock Special Economic Zone shows the opposite trajectory: its water body pixel count declined gradually as part of the zone was submerged between 2018 and 2020, after which the water body pixel count fell to zero and remained there through 2025. (2) Abdul Monem Economic Zone’s water body pixel count remained near zero throughout the series except for 10 px and 6 px in 2018 and 2020, respectively, an isolated fluctuation rather than a sustained trend.

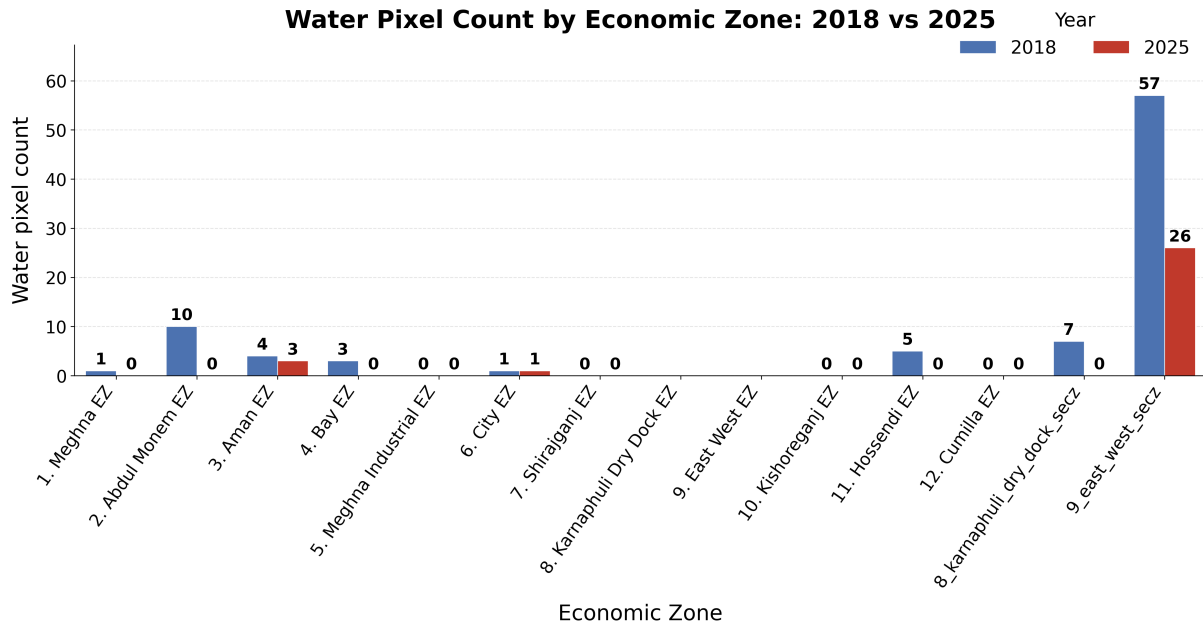


Figure 34: Water (LULC2) pixel count by economic zone, 2018 vs 2025.

The 2018-versus-2025 comparison in Figure 34 isolates the net change obscured by year-to-year fluctuation in the trend line above. (8) Karnaphuli Dry Dock Special Economic Zone shows the most pronounced shift in the dataset, moving from the highest water pixel count of any zone in 2018 to effectively zero by 2025, a direct visual confirmation of its shoreline submergence-then-reclamation pattern. (9) East West Special Economic Zone likewise shows a substantial net decline between the two endpoints, though its partial 2023–2025 recovery means the 2018–2025 gap is smaller than its intra-period minimum. The remaining ten zones show 2018 and 2025 bars of comparable, minimal height, confirming that water pixel count is structurally stable for the large majority of zones and is not a meaningful driver of overall land-cover change in this dataset.

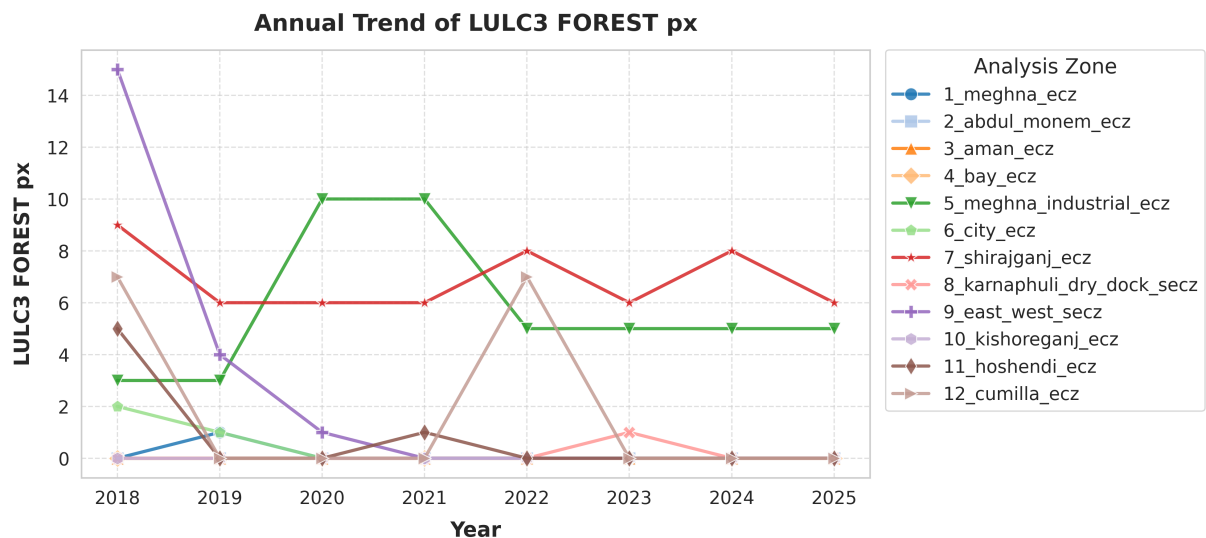


Figure 35: Annual trend of LULC3 Forest pixel count (2018–2025) across the twelve economic zones.

Forest pixel counts follow an equally narrow range zone-wide (Figure 35). (9) East West Special Economic Zone again stands out, recording the highest forest pixel count of any zone in 2018 (more than 14 px), which then declined sharply from 2018 to 2021 and

remained at 0 px through 2025 , consistent with the same rapid land-cover consolidation into built-up area described for this zone’s water and meadow trends. (7) Shirajganj Economic Zone’s forest cover stayed roughly unchanged at about 7–9 px across the full period, the most stable forest trajectory of any zone in the dataset. (5) Meghna Industrial Economic Zone shows a brief, self-reversing deviation from this stability, rising to about 10 px in 2020–2021 before settling back to 7 px, where it remained through 2025.

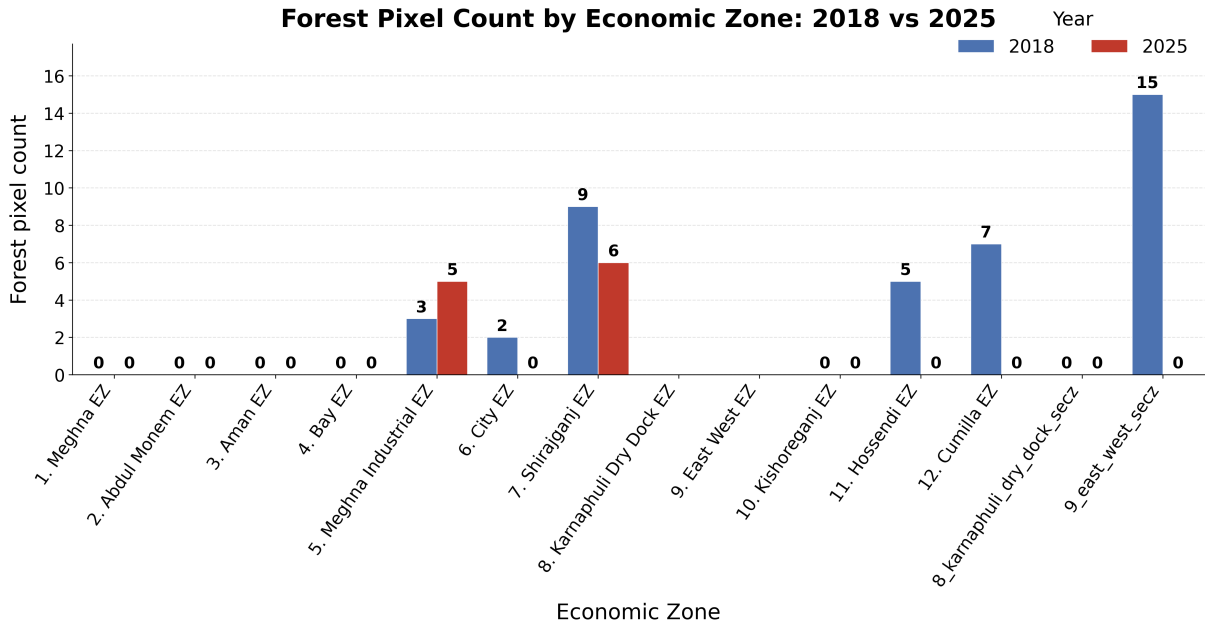


Figure 36: Forest (LULC3) pixel count by economic zone, 2018 vs 2025.

Figure 36 confirms this pattern at the two study endpoints. (9) East West Special Economic Zone shows the starkest contrast of any zone, falling from its 2018 peak to a 2025 value of zero, visually reinforcing its classification as the zone undergoing the most complete land-cover conversion in the dataset. (7) Shirajganj Economic Zone’s bars are nearly identical in height between 2018 and 2025, consistent with its description above as the most stable forest trajectory recorded. (5) Meghna Industrial Economic Zone’s 2018 and 2025 bars are also similar in height despite the intervening 2020–2021 rise, illustrating that its brief mid-period increase in forest cover was fully reversed rather than representing a lasting net change. All remaining zones show minimal, comparably sized bars in both years, indicating negligible forest-cover change at either endpoint.

6.2 Land Use Land Cover Parameters (Percentages)

This section reframes the LULC classes as a share of each zone’s total footprint rather than as raw pixel counts, covering the same three groupings used for the pixel-count series,built-up expansion; farmland and meadow, including the agrarian conversion and dual-source displacement pathways; and water and forest dynamics, across 2018–2025. Reading together, the percentage-based trends confirm the typology already established in the pixel-count series: urban-core consolidation into built-up land, direct farmland-to-meadow conversion in the agrarian zones, structural stability in a subset of zones, and site-geometry constraints on the coastal zone. At the same time, expressing each class as a proportion of a zone’s own footprint sharpens that typology in one specific way: zones with small total footprints, which appeared to show only minimal change when measured in absolute pixel terms, in fact underwent some of the largest proportional shifts in the

entire dataset. The subsections below work through each class in turn, pairing its annual percentage trend with its corresponding 2018-vs-2025 endpoint comparison.

6.2.1 Farmland and Meadow: Agrarian Conversion, Refined Zones, and Dual-Source Displacement

This subsection tracks farmland (LULC1) and meadow (LULC5) as percentages of zone footprint, first through their annual trajectories and then through their 2018-vs-2025 endpoints, to establish the timing and magnitude of the farmland-to-meadow conversion, confirm which zones stayed structurally stable, and identify proportional shifts in small-footprint zones that the pixel-count series could not isolate.

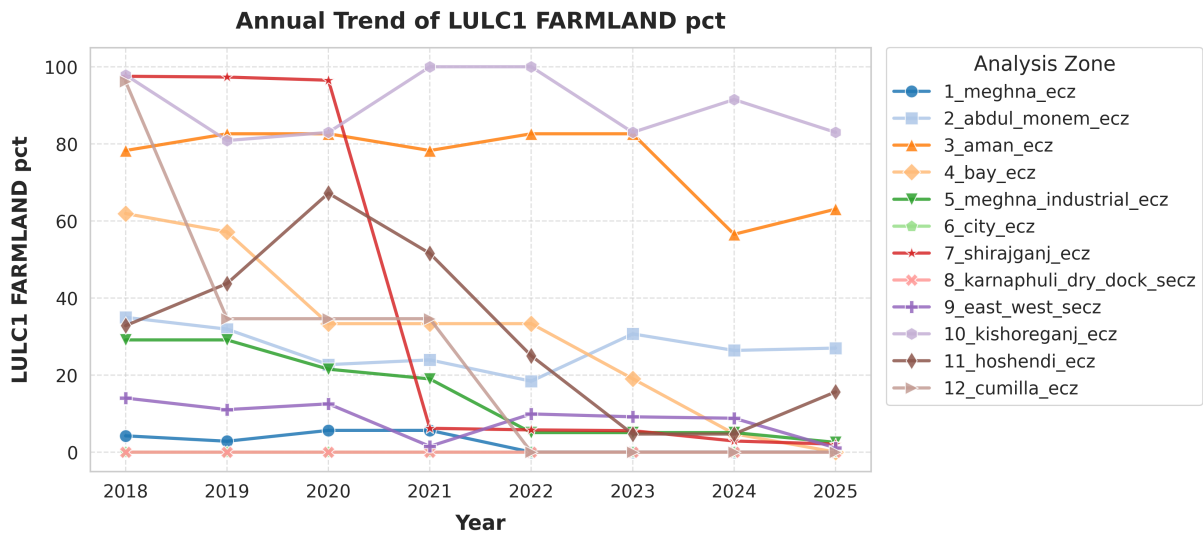


Figure 37: Annual trend of LULC1 Farmland percentage (2018-2025) across the twelve economic zones.

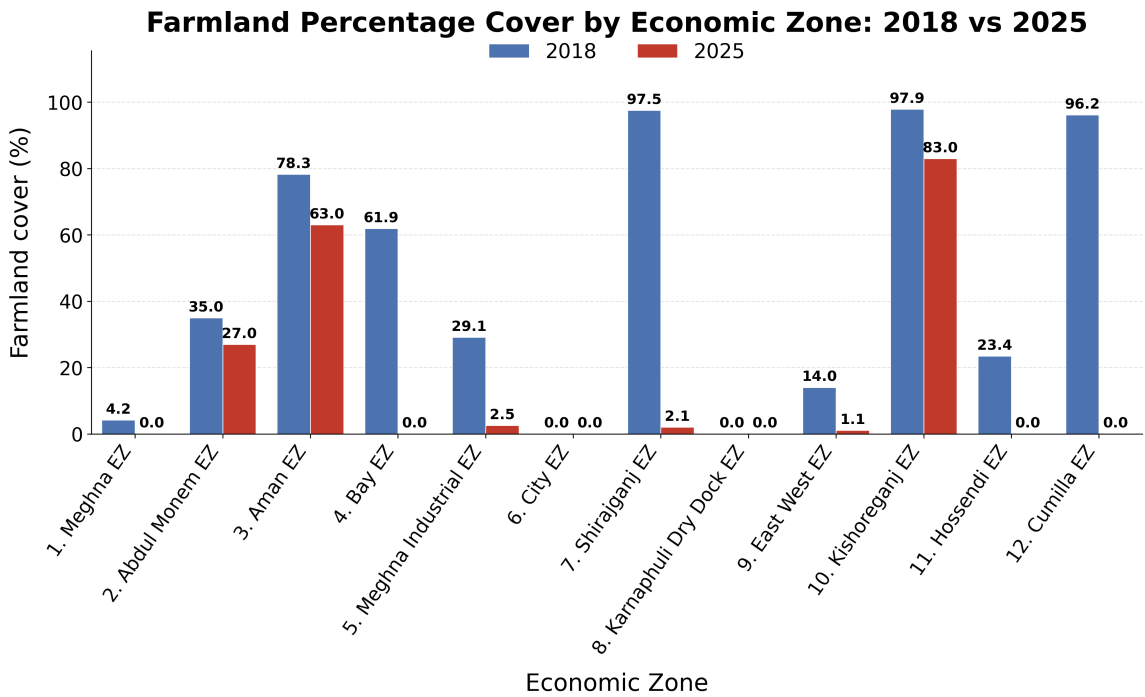


Figure 38: Farmland (LULC1) percentage cover by economic zone, 2018 vs 2025.

The farmland percentage series in Figure 37 confirms the direct farmland-to-meadow conversion identified in the pixel-count data, while resolving the earlier ambiguity around the exact timing of this transition for (12) Cumilla Economic Zone. (11) Hossaindi Economic Zone’s farmland trajectory declines from nearly 24% in 2018 to 0% in 2025. (7) Shirajganj Economic Zone held roughly 98% farmland from 2018 to 2020, which collapsed to below 5% in 2021 as meadow rose to occupy the same share. (12) Cumilla Economic Zone shows the same conversion: farmland fell from about 98% in 2018 to roughly 36% by 2019–2021 and to near 0% from 2022 onward, consistent with, and clarifying, the earlier pixel-count description of a 2019 meadow rise followed by a 2022 peak.

The 2018-versus-2025 comparison in Figure 38 makes this farmland loss visually explicit in proportional terms: (7) Shirajganj Economic Zone and (12) Cumilla Economic Zone both fall from close to a full 98% farmland cover in 2018 to near 0% by 2025, among the largest percentage-point collapses of any class in this study. (4) Bay Economic Zone and (5) Meghna Industrial Economic Zone show a comparably steep decline, from 62% and 30% respectively down to below 2%, a collapse the pixel-count bar chart could not reveal, since both zones were grouped there only as having “significantly lower to none” farmland throughout, rather than as undergoing an active farmland-to-built-up conversion over the study period. By contrast, (1) Meghna Economic Zone and (6) City Economic Zone maintained consistently low farmland across 2018–2025, below 5% and near 0% respectively, appearing as uniformly low bars in both years and confirming the pixel-count description of these two zones as having minimal farmland throughout rather than undergoing conversion. The percentage series also confirms the farmland stability identified in three agrarian zones, with specific bounds not available from pixel counts alone: (2) Abdul Monem Economic Zone, (10) Kishoreganj Economic Zone, and (3) Aman Economic Zone all maintained roughly constant farmland over 2018–2025, with the percentage never dropping by more than 20 percentage points in any of the three zones. (9) East West Special Economic Zone’s farmland fluctuations, noted but not quantified in the pixel-count series, are confirmed to have stayed below 18% throughout 2018–2025.

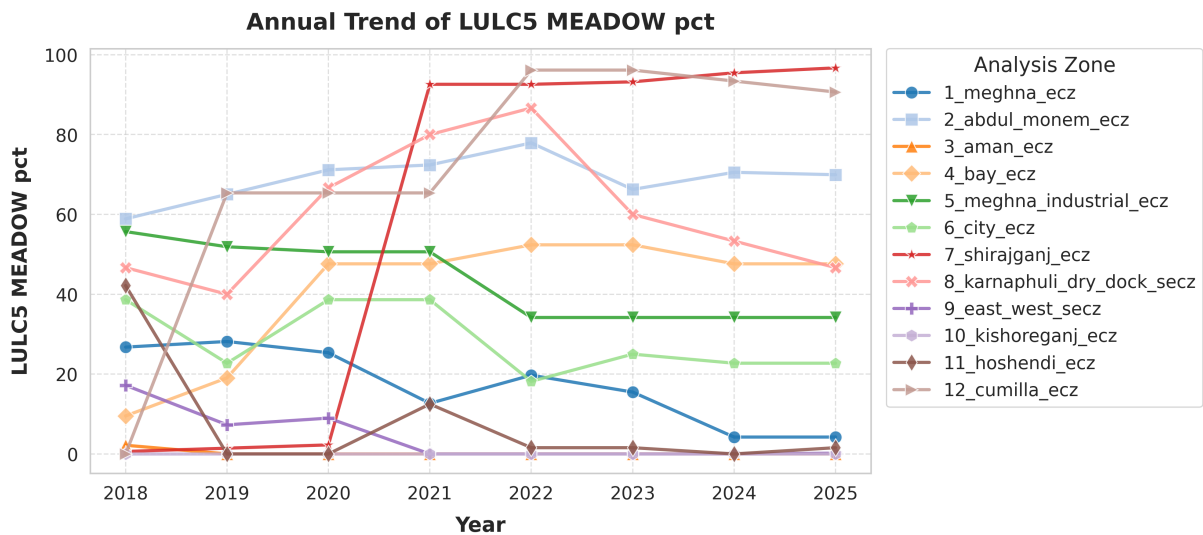


Figure 39: Annual trend of LULC5 Meadow percentage (2018–2025) across the twelve economic zones.

The meadow percentage series in Figure 39 adds several patterns with no counterpart in the pixel-count discussion, again concentrated in zones with small total footprints. (4) Bay Economic Zone’s meadow share rose from below 10% to nearly 50%, a proportionally substantial increase that the pixel-count series’ “minimal” grouping for the remaining zones

did not capture. (3) Aman Economic Zone and (10) Kishoreganj Economic Zone held minimal meadow share, near 0%, across most of the period, with the exception of (11) Hossaindi Economic Zone, which recorded the highest meadow share of the series, nearly 52%, in 2018, then the lowest, nearly 2%, in 2025. (5) Meghna Industrial Economic Zone's meadow share declined gradually from about 57% to 35%, confirming its pixel-count trend, while (6) City Economic Zone, not discussed in the pixel-count meadow trend, shows a comparable gradual decline from about 38% to 23%. (9) East West Special Economic Zone's meadow share fell drastically from 18% in 2018 to 0% by 2021 and remained near zero through 2025, confirming its pixel-count trajectory. (1) Meghna Economic Zone, also not discussed in the pixel-count meadow trend, shows a gradual meadow decline from 23% to 4% over the same period. (2) Abdul Monem Economic Zone held a meadow share of about 48% in both 2018 and 2025, rising to a substantially higher peak of 78% in 2021. (8) Karnaphuli Dry Dock Special Economic Zone shows the same non-monotonic shape at a higher level: its meadow share was about 59% in both 2018 and 2025, peaking at 84% in 2021.

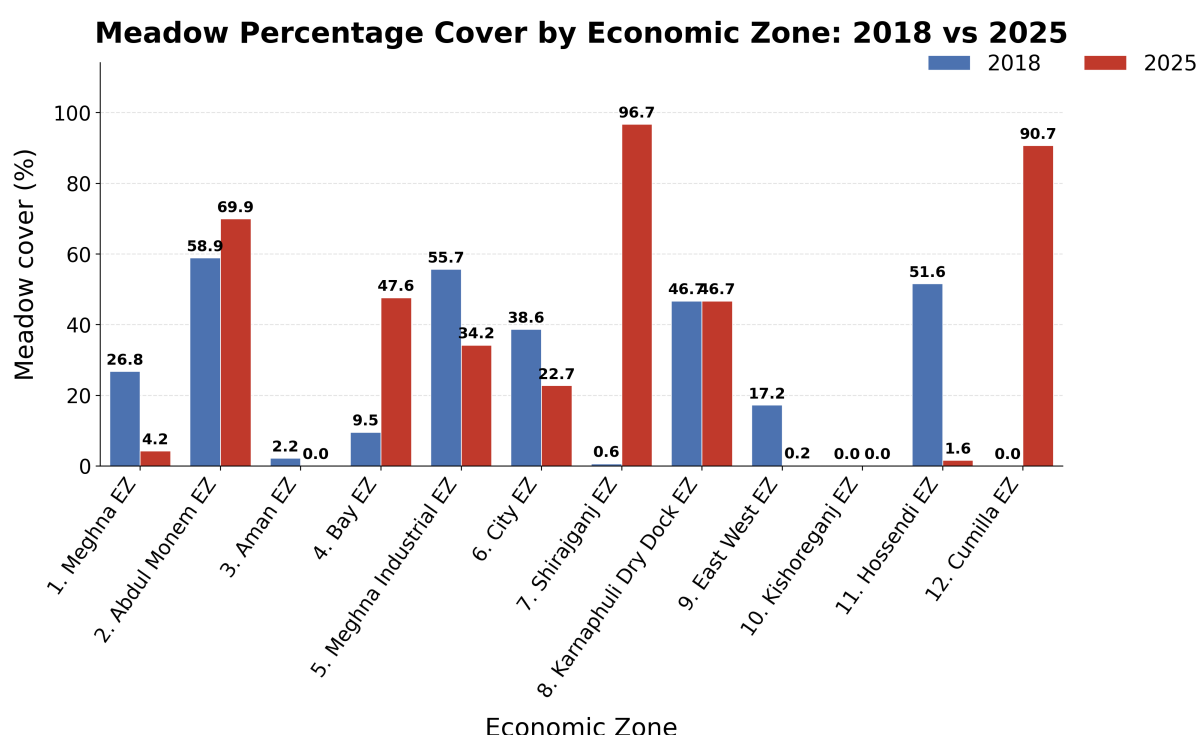


Figure 40: Meadow (LULC5) percentage cover by economic zone, 2018 vs 2025.

Figure 40 isolates the corresponding net meadow change at the two study endpoints. (7) Shirajganj Economic Zone and (12) Cumilla Economic Zone again show the largest gains in the dataset, mirroring their farmland losses in Figure 38 and confirming the lock-step conversion described above. (11) Hossaindi Economic Zone instead shows a net decline between the two years, from its 2018 high of nearly 52% to nearly 2% by 2025, despite the more volatile, non-monotonic path visible in Figure 39. (2) Abdul Monem Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone both show comparable bar heights in 2018 and 2025 (about 48% and 59% respectively), masking the substantially higher 2021 peaks visible only in the annual trend, a reminder that the endpoint comparison alone can understate a non-monotonic zone's true year-to-year variability.

6.2.2 Water and Forest Dynamics, Quantified

This subsection turns to water (LULC2) and forest (LULC3) as percentages of zone footprint, using the annual trend and endpoint comparison for each class to quantify site-geometry effects on the coastal zone and confirm the minimal, largely stable forest cover already suggested by the pixel-count series.

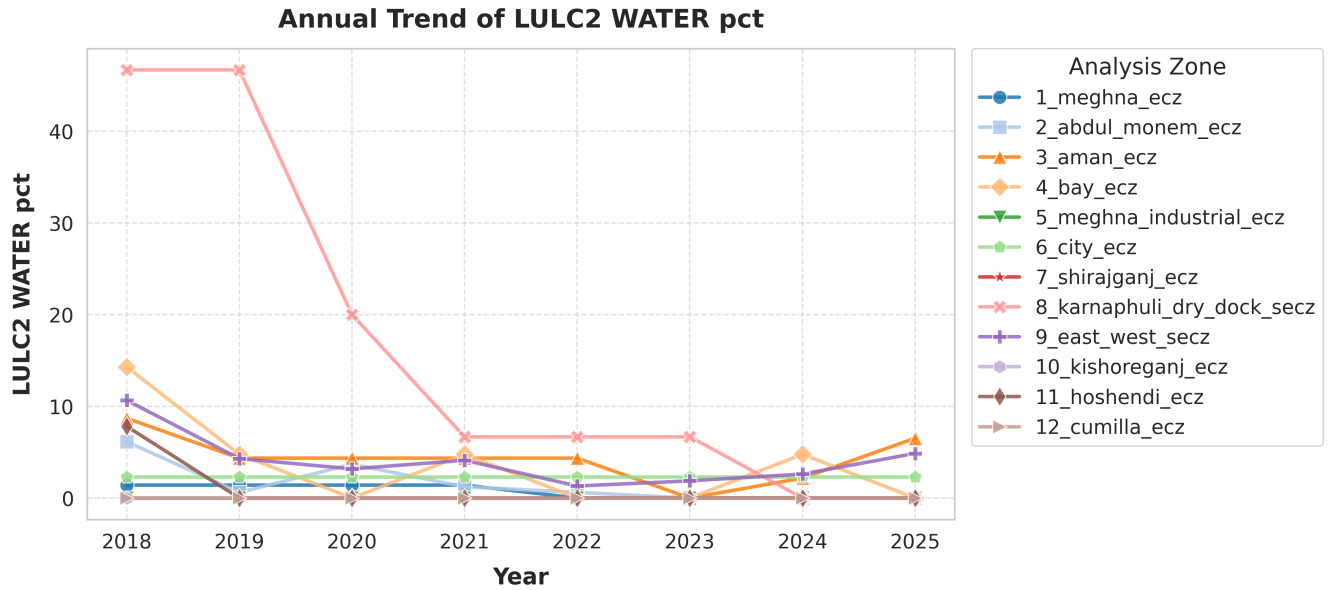


Figure 41: Annual trend of LULC2 Water percentage (2018–2025) across the twelve economic zones.

Site-geometry constraints on (8) Karnaphuli Dry Dock Special Economic Zone are clarified by the annual water percentage trend in Figure 41: the zone held the highest water share of any zone, more than 45% in 2018–19, consistent with the pixel-count description of part of the zone being submerged over the same interval, before declining gradually to 0% by 2024, a slightly more precise endpoint than, but not contradicting, the pixel-count series’ description of the water body being “gone” after 2020. (9) East West Special Economic Zone’s water share, the highest of any zone in 2018 at about 12%, declined to around 5% and remained near that level with fluctuations through 2025, consistent with the pixel-count description. A new data point emerges for (4) Bay Economic Zone, whose water share fell from 15% in 2018 to around 5% and remained near that level with fluctuations, a zone not separately discussed in the pixel-count water trend. The same trend also establishes a zone-wide bound not previously available: all zones held less than or nearly 10% water share in 2018, except for (4) Bay Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone (nearly 47%); all zones fall to nearly 5% or below from 2019 onward, except for (8) Karnaphuli Dry Dock Special Economic Zone, whose share remained elevated in that year; and from 2020 onward, consistent with, and quantifying, the pixel-count series’ earlier note, water proportion stayed under 10% zone-wide, while (8) Karnaphuli Dry Dock Special Economic Zone’s water share fell below 10% only from 2021 onward.

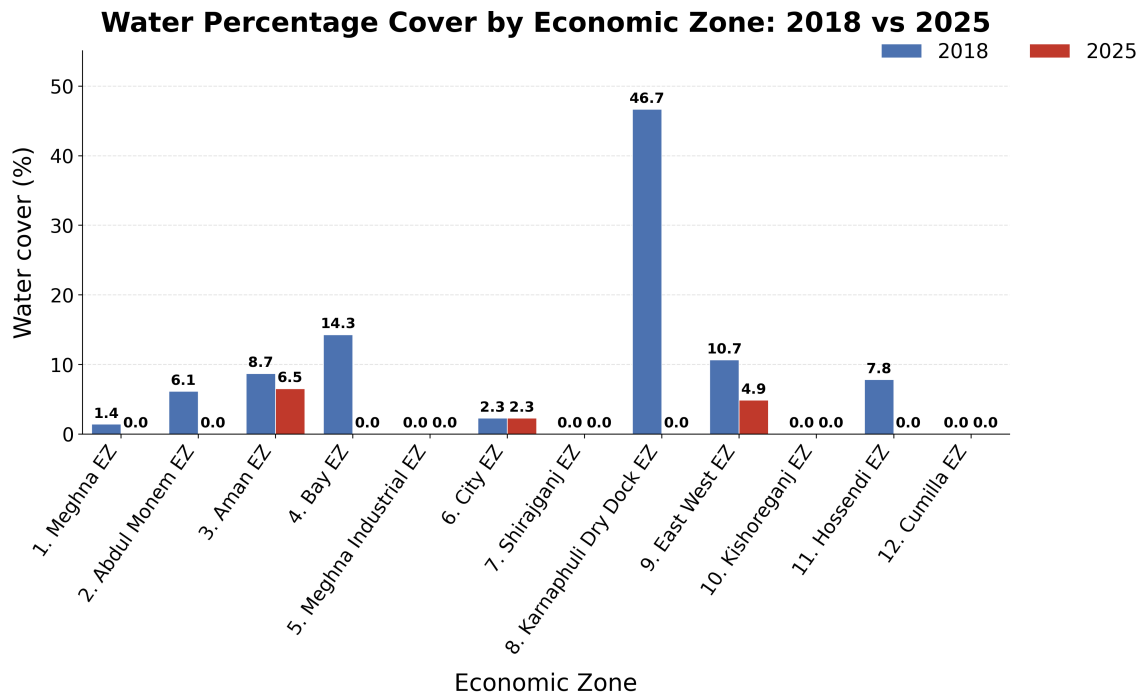


Figure 42: Water (LULC2) percentage cover by economic zone, 2018 vs 2025.

The 2018-versus-2025 comparison in Figure 42 isolates this decline at the two study endpoints: (8) Karnaphuli Dry Dock Special Economic Zone falls from the highest starting share in the dataset (nearly 47%) to 0%, and (4) Bay Economic Zone and (9) East West Special Economic Zone both fall from their comparatively elevated 2018 shares (15% and 12% respectively) to around 5%, while every other zone's bar remains close to its already-low 2018 level, confirming that the water-share decline over the study period is effectively confined to these three zones.

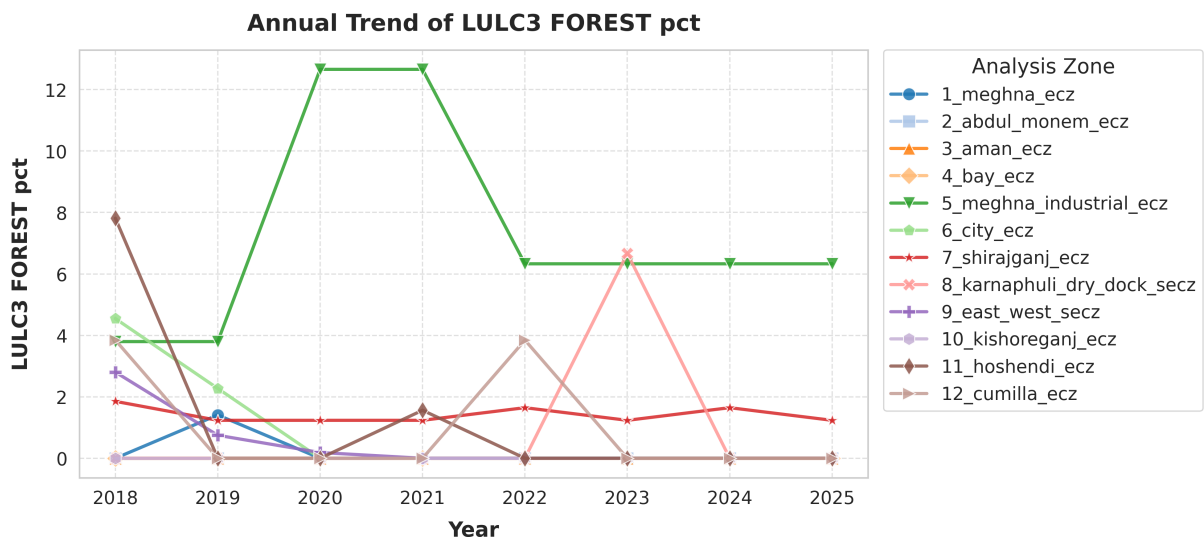


Figure 43: Annual trend of LULC3 Forest percentage (2018–2025) across the twelve economic zones.

The annual forest trend in Figure 43, minimal across all zones, is confirmed and quantified rather than contradicted by the pixel-count series: (9) East West Special Economic Zone recorded the highest forest share of any zone in 2018, just over 14%, declining sharply to 0% by 2021 and remaining there through 2025, matching its pixel-count trend. (7) Shirajganj Economic Zone's forest share remained roughly unchanged

at about 2% throughout, and (5) Meghna Industrial Economic Zone’s forest share rose to more than 12% in 2020–2021 before dropping to 6%, where it remained through 2025 , both consistent with their respective pixel-count trajectories. Across all zones, forest share stayed below 10% in 2018, and fell to 8% or below from 2019 onward, except for (5) Meghna Industrial Economic Zone.

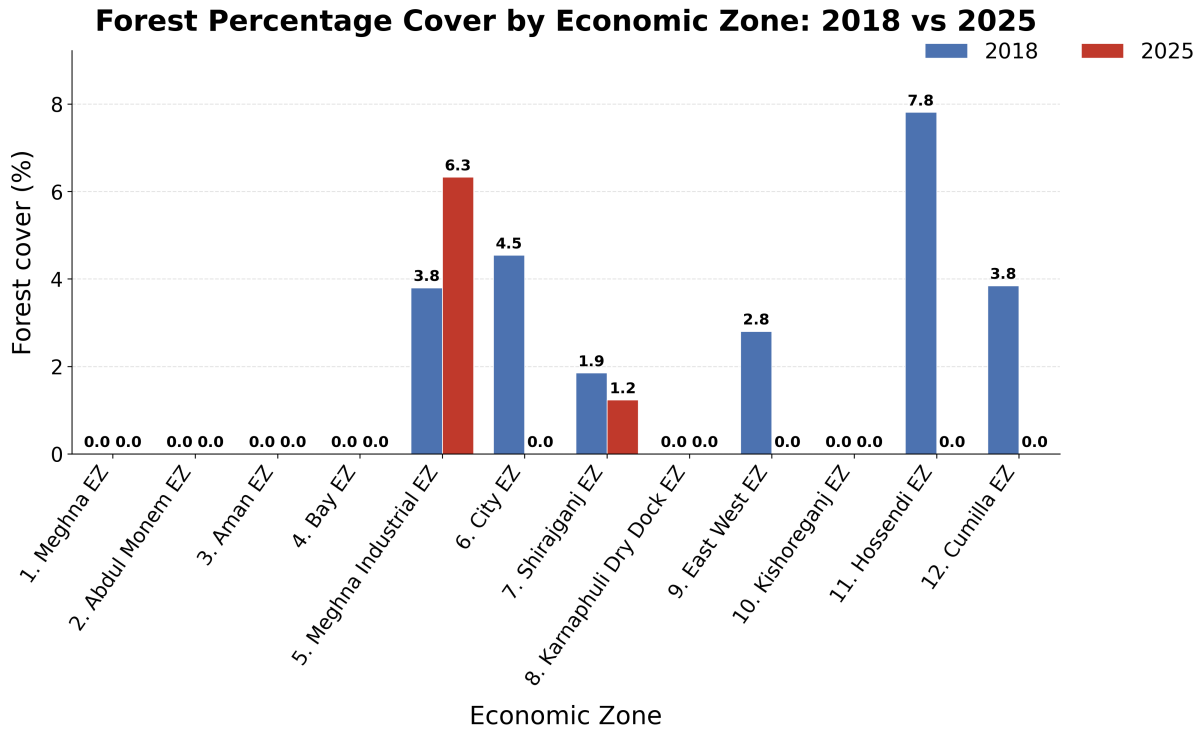


Figure 44: Forest (LULC3) percentage cover by economic zone, 2018 vs 2025.

The 2018-versus-2025 endpoint comparison in Figure 44 closes out the class: (9) East West Special Economic Zone’s bar falls from its 2018 high of just over 14% to 0%, and (5) Meghna Industrial Economic Zone’s bar settles at 6%, below its intervening 2020–2021 peak but still above its 2018 level , while every remaining zone’s bar stays essentially flat and near zero across both years, reflecting forest cover’s overall minimal role in this dataset.

6.3 Night-Time Lights (NTL) per SqKm Analysis

This section examines night-time-lights (NTL) intensity per square kilometer as an independent proxy for urbanization, first in raw form and then rescaled through min–max normalization for use in the composite urbanization indices of Section 4.9. Taken together, the two series show that annual NTL intensity (2018–2025) is broadly consistent with the built-up expansion patterns described in the preceding LULC subsections, while also revealing that NTL growth does not scale uniformly with built-up growth across zones , some zones register large lighting increases well beyond what their built-up growth alone would suggest, while at least one zone with the largest built-up increase in the dataset shows only a modest NTL rise.

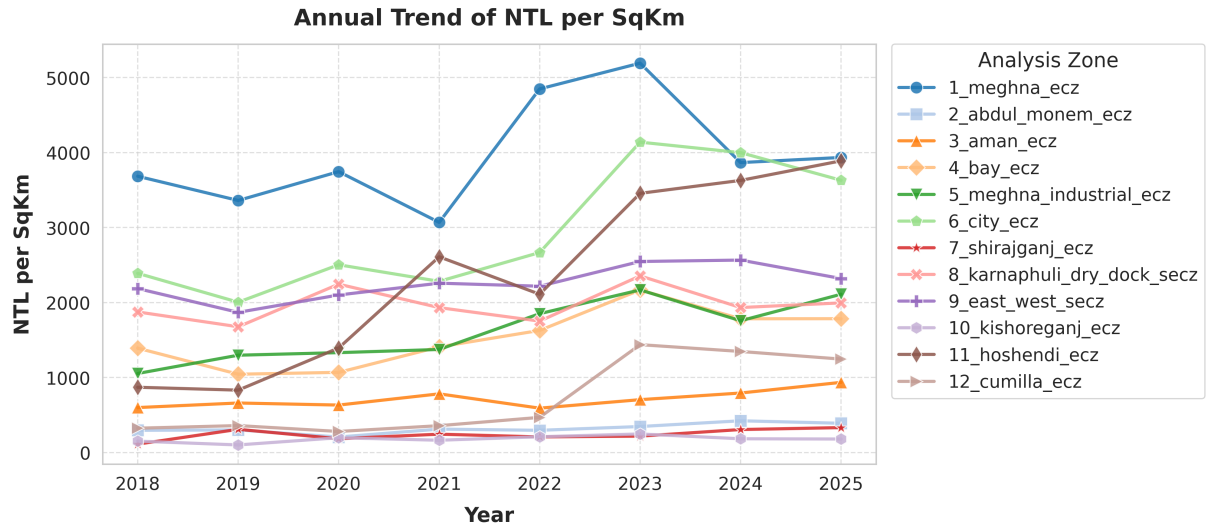


Figure 45: Annual trend of night-time-lights (NTL) intensity per square kilometer (2018–2025) across the twelve economic zones.

The raw NTL-per-km² trend in Figure 45 shows (2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, and (10) Kishoreganj Economic Zone with very minimal NTL change over 2018–2025, consistent with their low built-up shares and the absence of significant industrial activity. (9) East West Special Economic Zone is a notable exception to the general built-up–NTL relationship: despite recording the largest built-up increase of any zone in the LULC series, its NTL rose only modestly, likely because the zone is already surrounded by city lights and pre-existing industrial activity, leaving limited additional contrast for the sensor to register. (11) Hossaindi Economic Zone shows the most drastic NTL increase in the dataset, rising from roughly 900 to nearly 3900 NTL per sq. km, aligning with its sharp built-up growth from 2021 onward. (5) Meghna Industrial Economic Zone and (6) City Economic Zone show more moderate but still substantial increases, of roughly 1000 and 1300 NTL per sq. km respectively, consistent with their built-up growth over the same period. (8) Karnaphuli Dry Dock Special Economic Zone’s NTL fluctuates over time, reflecting the phased development of older and newer facilities, but shows little net increase overall (~100 NTL per sq. km). (3) Aman Economic Zone shows minimal NTL change, consistent with its minimal built-up growth. (1) Meghna Economic Zone shows a localized spike in 2022–23 in the zone’s western, low-built-up area, plausibly linked to construction activity, followed by a decline in 2024–25 once that construction concluded. (12) Cumilla Economic Zone shows a steady NTL rise plausibly tied to ongoing construction, followed by a decline that may correspond to construction wrapping up.

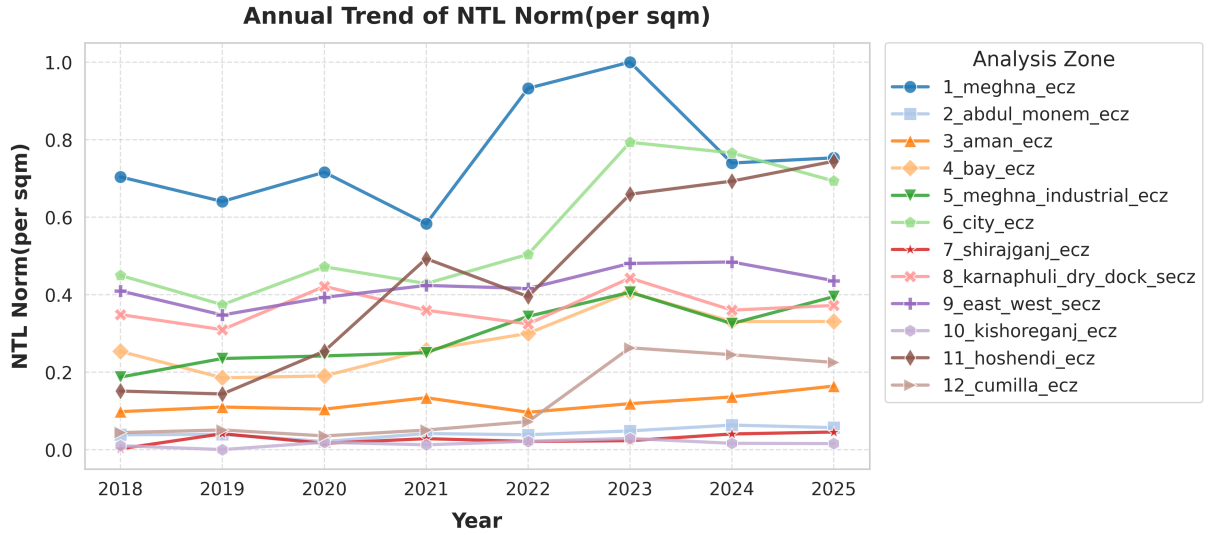


Figure 46: Annual trend of min–max normalized night-time-lights intensity (per square meter, 0–1 scale) (2018–2025) across the twelve economic zones. This normalized series feeds directly into the Urbanization Index constructions described in Section 4.9.

Figure 46 presents this same NTL series rescaled through longitudinal min–max normalization to a strict $[0, 1]$ range. The rescaling preserves the relative shape and ranking of each zone’s raw trajectory described above, (11) Hossaindi Economic Zone’s sharp rise, (8) Karnaphuli Dry Dock Special Economic Zone’s fluctuation-without-net-growth, and the near-flat lines for (2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (3) Aman Economic Zone, and (10) Kishoreganj Economic Zone all remain visible in normalized form, while removing the raw-value scale discrepancy between NTL and the percentage-based LULC series, allowing the two to be combined directly into the composite urbanization indices described in Section 4.9.

6.4 Population per SqKm Analysis

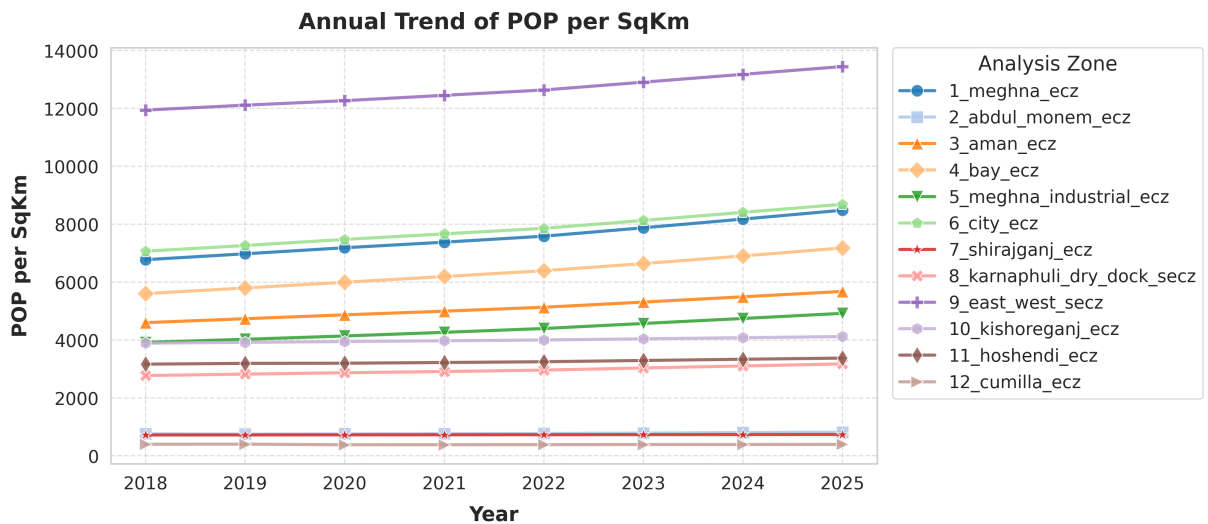


Figure 47: Annual trend of population density per square kilometer (2018–2025) across the twelve economic zones.

This section examines population density per square kilometer, again first in raw form and then min–max normalized for the composite urbanization indices of Section 4.9. The

annual trend (2018–2025) tracks closely with the built-up expansion patterns already identified in the LULC and NTL subsections, with population growth concentrated in the same urban-core zones that drove built-up and NTL gains, reinforcing rather than complicating the typology established so far.

The raw population-density trend in Figure 47 shows (7) Shirajganj Economic Zone, (2) Abdul Monem Economic Zone, and (12) Cumilla Economic Zone with very low population density and minimal change over the period, consistent with their low built-up growth among all twelve zones. (10) Kishoreganj Economic Zone holds a comparatively higher population density but shows little change over time, plausibly linked to its limited built-up development. (9) East West Special Economic Zone records the highest population density of any zone, rising in step with its built-up growth, consistent with its position within the city. (6) City Economic Zone and (1) Meghna Economic Zone likewise show population density increasing alongside their built-up growth. Population trends for the remaining zones were not individually distinguished in this analysis.

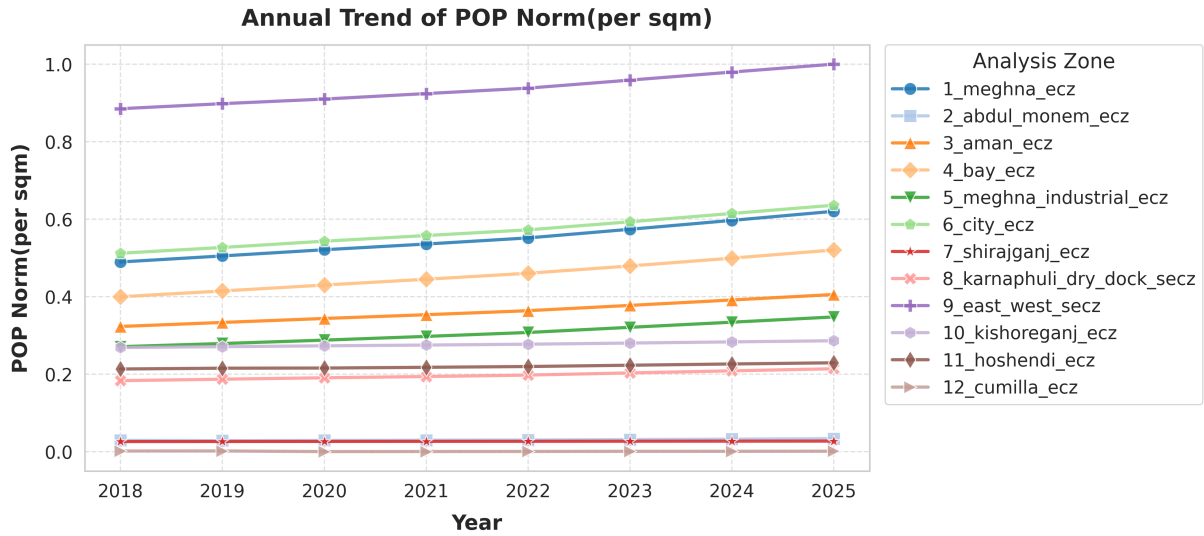


Figure 48: Annual trend of min–max normalized population density (per square meter, 0–1 scale) (2018–2025) across the twelve economic zones.

Figure 48 rescales this same population-density series to the $[0, 1]$ range via min–max normalization, preserving the ranking described above, (9) East West Special Economic Zone’s lead, the steady rises for (6) City Economic Zone and (1) Meghna Economic Zone, and the flat, low trajectories for (7) Shirajganj Economic Zone, (2) Abdul Monem Economic Zone, and (12) Cumilla Economic Zone, while placing population density on the same scale as the normalized NTL and percentage-based LULC series, so that it can be combined directly into the composite Urbanization Index constructions described in Section 4.9.

6.5 Development Indices

Building on the annual LULC, NTL, and population series presented above, the following results compare the three standardized development indices across the twelve economic zones from 2018 to 2025. The index construction, variable normalization, weighting, and mathematical formulations are defined in Chapter 4; the present section focuses on the resulting trajectories, levels, changes, and inter-zone patterns.

Table 10: Zone-wise development-index scores at the beginning and end of the study period, with documented physical-development start year. Index values are rounded to four decimal places; physical-development milestones follow the Development and Operational Chronology (Table 3).

Economic Zone	Physical Dev. Start	NUI		ECUI		NLDI	
		2018	2025	2018	2025	2018	2025
(1) Meghna Economic Zone	2016	0.7664	0.9927	0.6230	0.7770	0.7059	1.0000
(2) Abdul Monem Economic Zone	2016	0.0119	0.0376	0.0224	0.0403	0.0000	0.0320
(3) Aman Economic Zone	2016	0.1858	0.3501	0.1765	0.2912	0.1135	0.3178
(4) Bay Economic Zone	2016	0.2773	0.5695	0.2653	0.4583	0.1492	0.5469
(5) Meghna Industrial Economic Zone	2016	0.2003	0.5643	0.1906	0.4373	0.1190	0.5948
(6) City Economic Zone	by 2018	0.6163	0.8528	0.5023	0.6930	0.5695	0.7831
(7) Shirajganj Economic Zone	2019	0.0000	0.0135	0.0093	0.0242	0.0000	0.0000
(8) Karnaphuli Dry Dock Special Economic Zone	by 2019	0.1938	0.4946	0.1994	0.3731	0.0696	0.5569
(9) East West Special Economic Zone	by 2019	0.7225	1.0000	0.6159	0.7914	0.5777	0.9797
(10) Kishoreganj Economic Zone	by 2019	0.0893	0.1869	0.1000	0.1573	0.0044	0.1777
(11) Hossaindi Economic Zone	2020 onward	0.1595	0.7921	0.1527	0.6005	0.0979	0.8647
(12) Cumilla Economic Zone	before/by 2022	0.0053	0.1171	0.0151	0.1064	0.0000	0.0975

Note: NUI = Normalized Urbanization Index; ECUI = Equally Weighted Core Urbanization Index; NLDI = Normalized LULC Dynamics Index. The physical-development-start field is a contextual milestone and is not treated as the first year of the remote-sensing trajectory. The expressions “by 2018”, “by 2019”, “2020 onward”, and “before/by 2022” follow the evidence categories used in the Development and Operational Chronology.

Table 10 provides a compact endpoint comparison of the three development indices for all twelve economic zones. The table shows that the zones with the highest physical-development scores at the beginning of the study period are generally the same zones that remain at the upper end in 2025, while zones with lower baseline scores exhibit different rates of change. The table also makes the distinction between development stage and development trajectory explicit: the physical-development-start milestone comes from the institutional chronology, whereas NUI, ECUI, and NLDI are derived from the observed spatial data over 2018–2025. The indices should therefore be interpreted as complementary measures of observed development intensity rather than as direct measures of operational status.

6.5.1 Normalized Urbanization Index (NUI)

The Normalized Urbanization Index (NUI) provides the first comparative trajectory of development intensity across the twelve economic zones. The annual raw and normalized series are shown below.

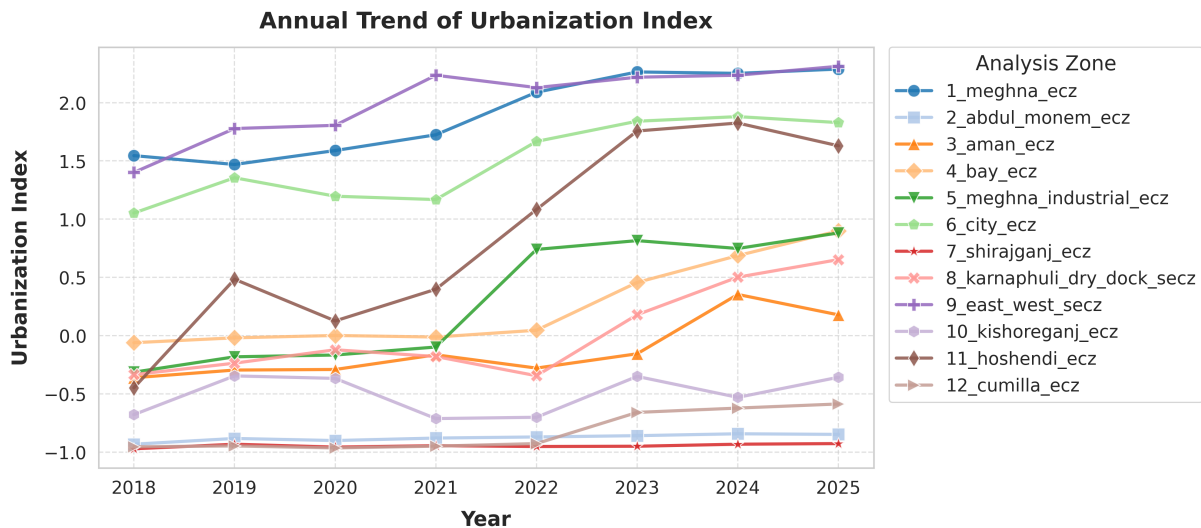


Figure 49: Annual trend of the raw Normalized Urbanization Index (NUI) component before final standardization (2018–2025) across the twelve economic zones.

As shown in Figure 49, the raw urbanization score ranges from approximately -1.0 to 2.5 across the study period. Zones located within the core urban corridor, such as (1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone, consistently plot toward the upper end, rising from approximately 1.0 – 1.5 in 2018 to above 2.0 by 2025. Conversely, zones such as (7) Shirajganj Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone remain near or below zero in several years, reflecting the dominance of agricultural and water-covered portions of their footprints during the earlier stages of development.

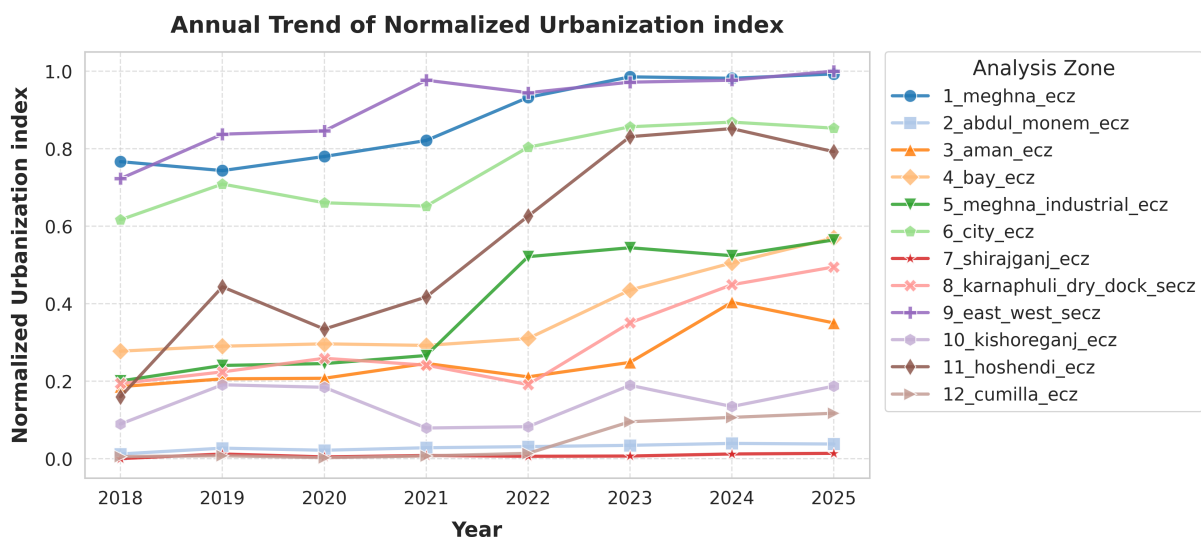


Figure 50: Annual trend of the Normalized Urbanization Index (NUI) (2018–2025) across the twelve economic zones.

The normalized NUI trajectories provide a direct inter-zone comparison of the relative urbanization state of each zone through time. (1) Meghna Economic Zone, (6) City

Economic Zone, and (9) East West Special Economic Zone occupy the upper portion of the trajectories throughout the period. (11) Hossaindi Economic Zone is distinguished by a sharp late-stage rise, while the remaining zones occupy lower or intermediate positions with differing rates of change.

The longitudinal plot was used to identify four distinct observed trajectory groupings, supported by K-Means clustering with $k = 4$ on the standardized eight-year trajectories. The clusters are not administrative units; they represent groups of economic zones with similar longitudinal development behavior. *Cluster 1* groups (1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone. *Cluster 2* contains (11) Hossaindi Economic Zone, distinguished by its unusually strong late-stage increase. *Cluster 3* brings together (3) Aman Economic Zone, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, and (8) Karnaphuli Dry Dock Special Economic Zone. *Cluster 4* comprises (2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (10) Kishoreganj Economic Zone, and (12) Cumilla Economic Zone.

6.5.2 Equally Weighted Core Urbanization Index (ECUI)

The Equally Weighted Core Urbanization Index (ECUI) emphasizes the three positive anthropogenic dimensions of development, built-up proportion, nighttime-light intensity, and population density, without subtracting the remaining LULC components. Its annual trajectory is shown in Figure 51.

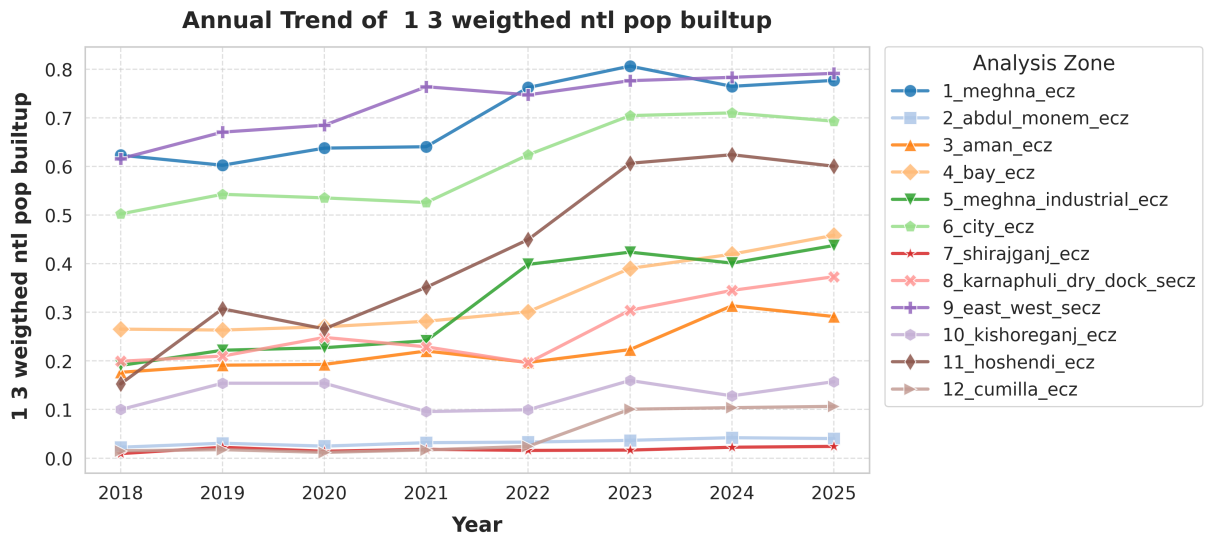


Figure 51: Annual trend of the Equally Weighted Core Urbanization Index (ECUI) (2018–2025) across the twelve economic zones.

The three zones, (1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone, consistently occupy the upper end of the ECUI throughout 2018–2025. (1) Meghna Economic Zone opens with the highest 2018 value in the dataset (0.623), dips slightly to 0.602 in 2019, then climbs to a peak of 0.806 in 2023 before settling at 0.777 by 2025. (9) East West Special Economic Zone rises almost monotonically from 0.616 in 2018 to a dataset-wide high of 0.791 in 2025, while (6) City Economic Zone follows a similar upward path from 0.502 in 2018 to a peak of 0.710 in 2024 before easing slightly to 0.693 in 2025.

The most pronounced single-zone change in the ECUI belongs to (11) Hossaindi Economic Zone, which rises from 0.153 in 2018 to 0.600 in 2025, a net increase of 0.448. This increase is driven by a sustained rise through the later years of the study period.

A mid-range group, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, (8) Karnaphuli Dry Dock Special Economic Zone, and (3) Aman Economic Zone, starts 2018 clustered between 0.177 and 0.265 and moves to between 0.291 and 0.458 by 2025. Within this group, (5) Meghna Industrial Economic Zone posts a net gain of 0.247, rising from 0.191 to 0.437, while (3) Aman Economic Zone posts the smallest gain, rising from 0.177 to 0.291 after briefly peaking at 0.313 in 2024.

The remaining four zones, (10) Kishoreganj Economic Zone, (12) Cumilla Economic Zone, (2) Abdul Monem Economic Zone, and (7) Shirajganj Economic Zone, remain below 0.2 throughout the period. (10) Kishoreganj Economic Zone oscillates between 0.096 and 0.160 and ends 2025 only 0.057 above its 2018 value. (12) Cumilla Economic Zone remains near-flat through 2022 before rising to approximately 0.101–0.106 in 2023–2025. (2) Abdul Monem Economic Zone and (7) Shirajganj Economic Zone show the least change, with (7) Shirajganj Economic Zone ending 2025 at 0.024, a net increase of only 0.015.

6.5.3 Normalized LULC Dynamics Index (NLDI)

The Normalized LULC Dynamics Index (NLDI) isolates the physical land-cover transformation component of development. The raw trajectory is shown first, followed by the standardized series used for inter-zone comparison.

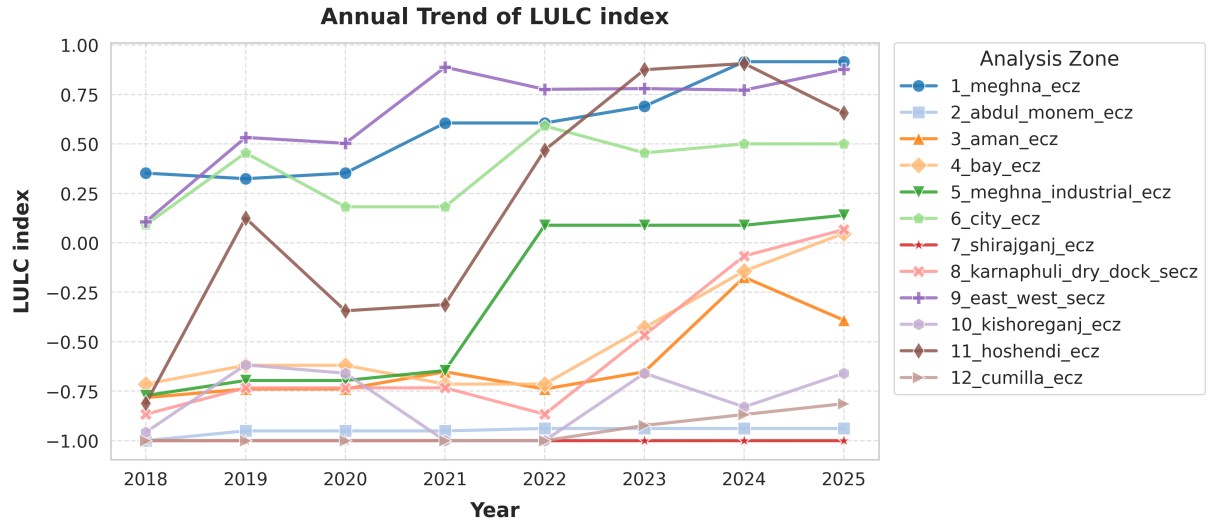


Figure 52: Annual trend of the raw LULC transformation score underlying the Normalized LULC Dynamics Index (NLDI) (2018–2025) across the twelve economic zones.

The empirical trajectory of the raw LULC transformation score across the twelve economic zones from 2018 to 2025 is illustrated in Figure 52. The overall dataset mean rose from -0.6130 in 2018 to -0.0501 in 2025, indicating a substantial shift in the balance of classified land cover toward built-up surfaces across the economic-zone footprints.

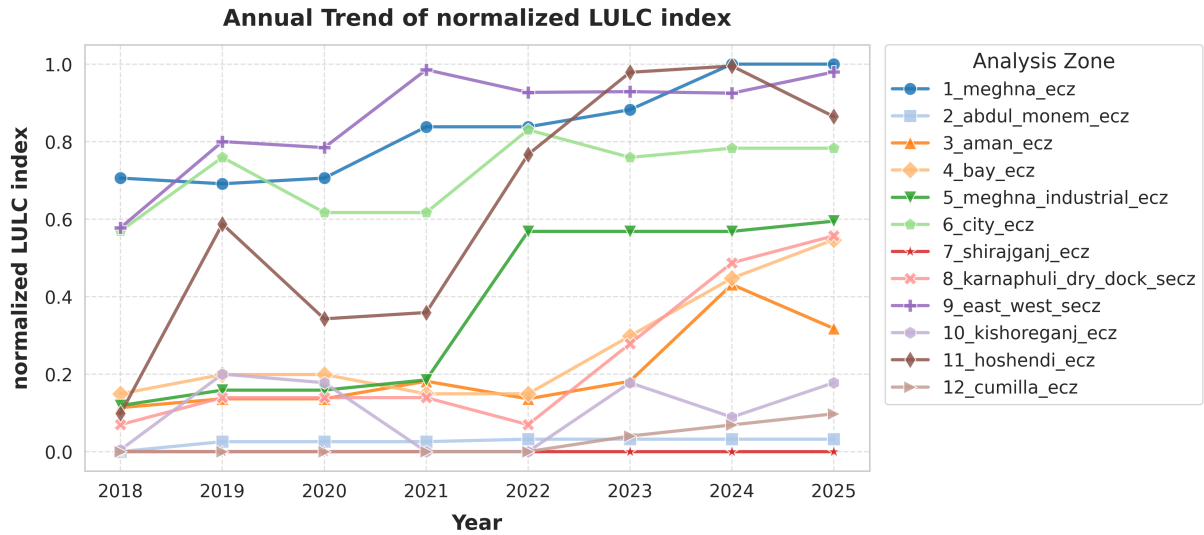


Figure 53: Annual trend of the Normalized LULC Dynamics Index (NLDI) (2018–2025) across the twelve economic zones.

As Figure 53 shows, (11) Hossaindi Economic Zone records the strongest rise, increasing from 0.0979 in 2018 to 0.8647 in 2025, a net increase of 0.7668. Its trajectory reaches a higher value of approximately 0.995 in 2024 before easing in 2025. (1) Meghna Economic Zone and (9) East West Special Economic Zone also remain near the upper end of the standardized scale, increasing from 0.7059 and 0.5777 in 2018 to 1.0000 and 0.9797 in 2025, respectively. (6) City Economic Zone increases from 0.5695 in 2018 to 0.7831 in 2025.

The transition zones also show substantial relative change. (5) Meghna Industrial Economic Zone increases from 0.1190 in 2018 to 0.5948 in 2025. (4) Bay Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone increase from 0.1492 and 0.0696 to 0.5469 and 0.5569, respectively, while (3) Aman Economic Zone rises from 0.1135 to 0.3178.

Conversely, (7) Shirajganj Economic Zone remains at 0.0000 throughout the eight-year period. (2) Abdul Monem Economic Zone increases from 0.0000 in 2018 to 0.0320 in 2025, while (12) Cumilla Economic Zone rises from 0.0000 to 0.0975. (10) Kishoreganj Economic Zone increases from 0.0044 in 2018 to 0.1777 in 2025.

6.6 Discussion

The inter-zone comparison of the Normalized Urbanization Index (NUI), Equally Weighted Core Urbanization Index (ECUI), and Normalized LULC Dynamics Index (NLDI) consistently groups the twelve economic zones into the same four clusters. **Cluster 1** contains three zones located within the Dhaka–Narayanganj urban core, (1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone and records the highest scores on every index throughout 2018–2025. **Cluster 2** contains a single zone, (11) Hossaindi Economic Zone, which is treated separately because it has no sibling zones to compare against, and which records the largest net change of any zone in the dataset on every index. **Cluster 3** groups four zones: (3) Aman Economic Zone, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, and (8) Karnaphuli Dry Dock Special Economic Zone, which begin from a broadly similar low-to-moderate 2018 baseline but diverge substantially by 2025. **Cluster 4** groups the four lowest-intensity zones in the dataset: (2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (10) Kishoreganj Economic Zone, and (12) Cumilla Economic Zone; all of which remain close to the floor of each index across the study period.

The four clusters represent observed longitudinal development patterns among the twelve economic zones, rather than administrative spatial groups. They were derived from the index trajectories using K-Means clustering with $k = 4$, supported by the comparative clustering plots. In practical terms, the groups distinguish zones that are already highly urbanized and remain high, zones that begin lower but exhibit rapid growth, zones with intermediate or diverging trajectories, and zones that remain comparatively low throughout the study period. This classification is separate from the five Upazila Group (UG) Zones used as spatial acquisition and processing supersets.

While this cluster membership is stable across all three indices, the magnitude, ranking, and shape of each zone’s trajectory differ depending on which underlying variables the index blends together. The three subsections below discuss each index’s cluster-level results in turn, drawing on the summary statistics that accompany the corresponding graphs in Section 4.9, and close with a short comparison of how the three measures agree and diverge.

6.7 Findings for the Normalized Urbanization Index (NUI)

This section presents the cluster-level findings for the Normalized Urbanization Index (NUI). The standardized indices are interpreted on the common 0–1 presentation scale described at the beginning of Chapter 6; higher values indicate greater relative development intensity within the observed dataset. Table 11 summarizes each cluster’s mean, minimum, maximum, and dispersion in 2018 and 2025, alongside a χ^2 measure of how linear each cluster’s growth path has been; Figure 45 traces each cluster’s mean trajectory and Min–Max band across the full study period. Across every cluster, the index’s rise between 2018 and 2025 corresponds to an actual, physical intensification of urbanization within these zones, not a statistical artifact of rescaling, as built-up land, population density, and night-time lights have genuinely expanded in step with the index. Cluster 1 ((1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone), all situated within the Dhaka–Narayanganj urban core, holds the highest scores throughout, rising from a mean of 0.702 in 2018 to 0.949 in 2025, with (9) East West Special Economic Zone reaching the maximum possible score of 1.000 by 2025. Cluster 2,

the single-zone case of (11) Hossaindi Economic Zone, records the largest net change of any zone in the dataset (0.633), driven by a late, sharp surge in built-up conversion after 2022 following an initial 2020–2021 contraction. Cluster 3 ((3) Aman Economic Zone, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, and (8) Karnaphuli Dry Dock Special Economic Zone) starts from a tightly clustered low-to-moderate baseline in 2018 and diverges substantially by 2025, with three of the four zones crossing the 50% built-up threshold while (3) Aman Economic Zone plateaus at 30%. Cluster 4 ((2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (10) Kishoreganj Economic Zone, and (12) Cumilla Economic Zone) remains the lowest-scoring group throughout, with all four zones staying under a 20% built-up ceiling and only (10) Kishoreganj Economic Zone, buoyed by a denser surrounding population, posting a meaningfully higher score than its cluster peers.

Cluster	Zones	Mean textbf{2018}	Mean textbf{2025}	Min textbf{(2018)}	Max textbf{(2018)}	Min textbf{(2025)}	Max textbf{(2025)}	Min–Max textbf{2018}	Min–Max textbf{2025}	Raw χ^2 textbf{(\Sigma)}
C1	1, 6, 9	0.702	0.949	0.616	0.766	0.853	1.000	0.150	0.147	0.064
C2	11	0.159	0.792	0.159	0.159	0.792	0.792	–	–	0.119
C3	3, 4, 5, 8	0.214	0.495	0.186	0.277	0.350	0.570	0.092	0.219	0.126
C4	2, 7, 10, 12	0.027	0.089	0.000	0.089	0.014	0.187	0.089	0.173	0.028

Table 11: Cluster-level summary of the Normalized Urbanization Index (2018–2025).

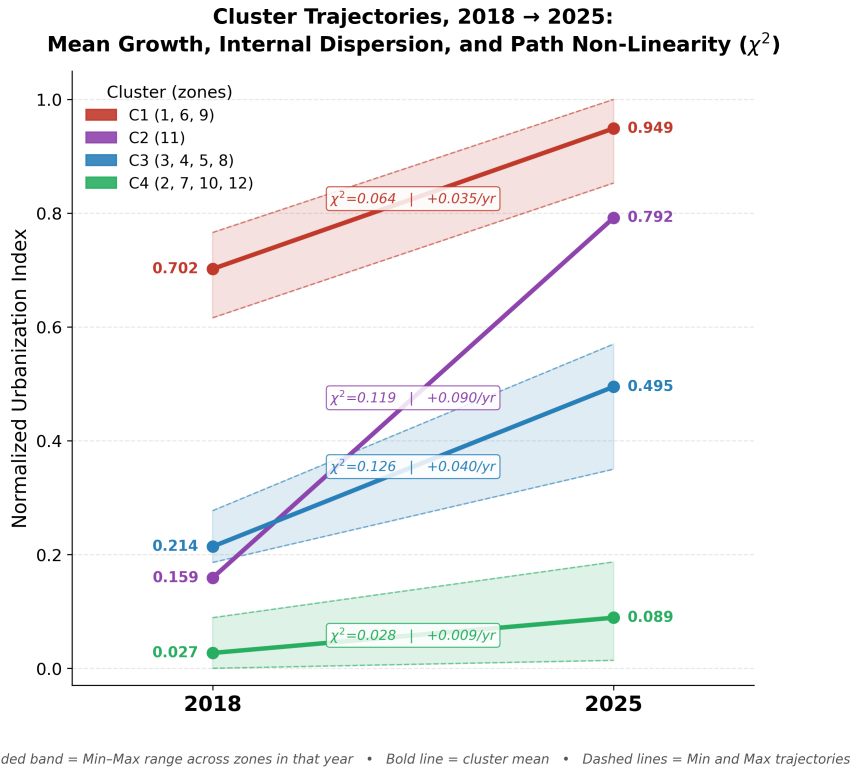


Figure 54: Cluster-level trajectories of the Normalized Urbanization Index (NUI) from 2018 to 2025. The bold line marks each cluster’s mean and its average annual rate of change; the shaded band spans its Min–Max range in each year; and the annotated χ^2 value indicates how far each cluster’s actual path deviated from a straight line between its 2018 and 2025 means.

6.8 Findings for the Equally Weighted Core Urbanization Index (ECUI)

This section presents cluster-level findings for the Equally Weighted Core Urbanization Index (ECUI), the composite metric that averages built-up percentage, normalized NTL intensity, and normalized population density in equal thirds, without subtracting remaining natural or agricultural land cover. The same four clusters identified under the Normalized Urbanization Index reappear here with an identical zone membership, allowing direct comparison of how the two indices rank and rate the same twelve zones. Table 12 reports each cluster’s mean, minimum, maximum, dispersion, and χ^2 linearity statistics on this index for 2018 and 2025.

Cluster	Zones	Mean textbf{2018}	Mean textbf{2025}	Min textbf{(2018)}	Max textbf{(2018)}	Min textbf{(2025)}	Max textbf{(2025)}	Min–Max textbf{2018}	Min–Max textbf{2025}	Raw χ^2 textbf{(\Sigma)}
C1	1, 6, 9	0.580	0.754	0.502	0.623	0.693	0.791	0.121	0.098	0.033
C2	11	0.153	0.600	0.153	0.153	0.600	0.600	–	–	0.036
C3	3, 4, 5, 8	0.208	0.390	0.177	0.265	0.291	0.458	0.089	0.167	0.044
C4	2, 7, 10, 12	0.037	0.082	0.009	0.100	0.024	0.157	0.091	0.133	0.011

Table 12: Cluster-level summary of the Equally Weighted Core Urbanization Index (ECUI) (2018–2025).

Zones: 1=Meghna, 2=Abdul Monem, 3=Aman, 4=Bay, 5=Meghna Ind., 6=City, 7=Shirajganj, 8=KDDSZ, 9=East West, 10=Kishoreganj, 11=Hossaindi, 12=Cumilla. Cluster 2 has only one zone, so cross-zone Min–Max is not applicable (shown as ,); its own 2018–2025 trajectory range (max – min across all 8 years) is 0.471. Mean/Min–Max values here are computed on the Equally Weighted Core Urbanization Index (ECUI).

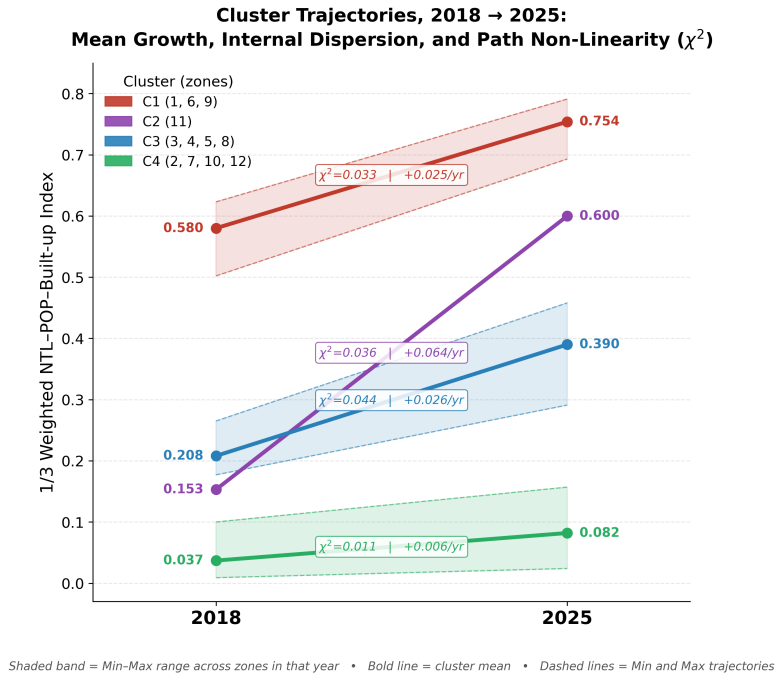


Figure 55: Cluster-level trajectories of the Equally Weighted Core Urbanization Index (ECUI) from 2018 to 2025. The bold line marks each cluster’s mean and its average annual rate of change; the shaded band spans its Min–Max range in each year; and the annotated χ^2 value indicates how far each cluster’s actual path deviated from a straight line between its 2018 and 2025 means.

Figure 55 traces each cluster’s mean trajectory and Min–Max dispersion band across the full study period. As with the Normalized Urbanization Index, the rise in this index across every cluster corresponds to genuine urbanization within these zones, built-up expansion, population growth, and increased night-time lighting all moving together over 2018–2025, though the composite consistently reports lower 2025 levels than the NUI, since population and light-emission growth in these zones has not fully kept pace with physical built-up conversion.

Cluster 1 ((1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone) again holds the highest scores throughout, rising from a mean of 0.580 in 2018 to 0.754 in 2025, though both figures sit below the equivalent Normalized Urbanization Index means, and (6) City Economic Zone posts the largest net gain of the three zones despite starting lowest. Cluster 2, the single-zone case of (11) Hossaindi Economic Zone, again records the largest single-zone increase in the dataset (net change 0.448), though this is smaller than its 0.633 net change on the NUI, since population and NTL growth here did not spike as sharply as built-up conversion. Cluster 3 ((3) Aman Economic Zone, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, and (8) Karnaphuli Dry Dock Special Economic Zone) again shows the widest internal divergence, with (5) Meghna Industrial Economic Zone posting the largest net change (0.247) and (3) Aman Economic Zone the smallest (0.115), a ranking consistent with the Normalized Urbanization Index and suggesting built-up expansion, rather than population or lighting growth specifically, drives the differences within this cluster. Cluster 4 ((2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (10) Kishoreganj Economic Zone, and (12) Cumilla Economic Zone) remains the flattest, lowest-baseline group, though here (12) Cumilla Economic Zone’s net change (0.091) exceeds (10) Kishoreganj Economic Zone’s (0.057) even though Kishoreganj holds the highest absolute level in both years, a reversal from the NUI, where Kishoreganj recorded the cluster’s largest net change.

6.9 Findings for the Normalized LULC Dynamics Index (NLDI)

This section presents cluster-level findings for the Normalized LULC Dynamics Index (NLDI), the LULC-based physical land-transformation index that isolates the physical land-cover dimension from the population and nighttime-lights signals used in the other two indices. The same four clusters identified under the Normalized Urbanization Index and the Equally Weighted Core Urbanization Index (ECUI) reappear here with an identical zone membership, allowing a three-way comparison of how each index rates the same twelve zones. Table 13 reports each cluster’s mean, minimum, maximum, dispersion, and χ^2 linearity statistics on this index for 2018 and 2025.

Figure 56 traces each cluster’s mean trajectory and Min–Max dispersion band across the full study period. Because this index isolates the LULC-based physical land-transformation signal, without the population and nighttime-lights components used in NUI and ECUI, the rise recorded in every cluster reflects direct, physical land-cover conversion within these zones and its year-to-year path is visibly more step-like and less smooth than either of the other two indices, since individual classification-year jumps are not moderated by any other input variable.

Cluster 1 ((1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone) posts the highest 2025 cluster mean recorded across all three indices in this study (0.921), with (1) Meghna Economic Zone reaching the absolute ceiling of the scale (1.000) by 2025. Cluster 2, the single-zone case of (11) Hossaindi Economic

Zone, records the largest net gain of any zone on any of the three indices (0.767) and the most erratic, non-monotonic trajectory in the entire study, with a raw χ^2 far exceeding any other zone's.

Cluster	Zones	Mean textbf{2018}	Mean textbf{2025}	Min textbf{(2018)}	Max textbf{(2018)}	Min textbf{(2025)}	Max textbf{(2025)}	Min–Max textbf{2018}	Min–Max textbf{2025}	Raw χ^2 textbf{(\Sigma)}
C1	1, 6, 9	0.618	0.921	0.570	0.706	0.783	1.000	0.136	0.217	0.173
C2	11	0.098	0.865	0.098	0.098	0.865	0.865	–	–	0.372
C3	3, 4, 5, 8	0.113	0.504	0.070	0.149	0.318	0.595	0.080	0.277	0.337
C4	2, 7, 10, 12	0.001	0.077	0.000	0.004	0.000	0.178	0.004	0.178	0.076

Table 13: Cluster-level summary of the Normalized LULC Dynamics Index (NLDI) (2018–2025).

Zones: 1=Meghna, 2=Abdul Monem, 3=Aman, 4=Bay, 5=Meghna Ind., 6=City, 7=Shirajganj, 8=KDDSZ, 9=East West, 10=Kishoreganj, 11=Hossaindi, 12=Cumilla. Cluster 2 has only one zone, so cross-zone Min–Max is not applicable (shown as ,); its own 2018–2025 trajectory range (max – min across all 8 years, peaking in 2024) is 0.897, the widest of any single zone across all three indices. The Cluster 4 normalized average excludes (7) Shirajganj Economic Zone, whose net change is exactly zero (flat at 0.000 across all 8 years), making its normalized ratio undefined; across the remaining three zones the average is skewed upward by (10) Kishoreganj Economic Zone (normalized value 2.26), and the median (1.12) is more representative. Mean/Min–Max values here are computed on the Normalized LULC Dynamics Index (NLDI).

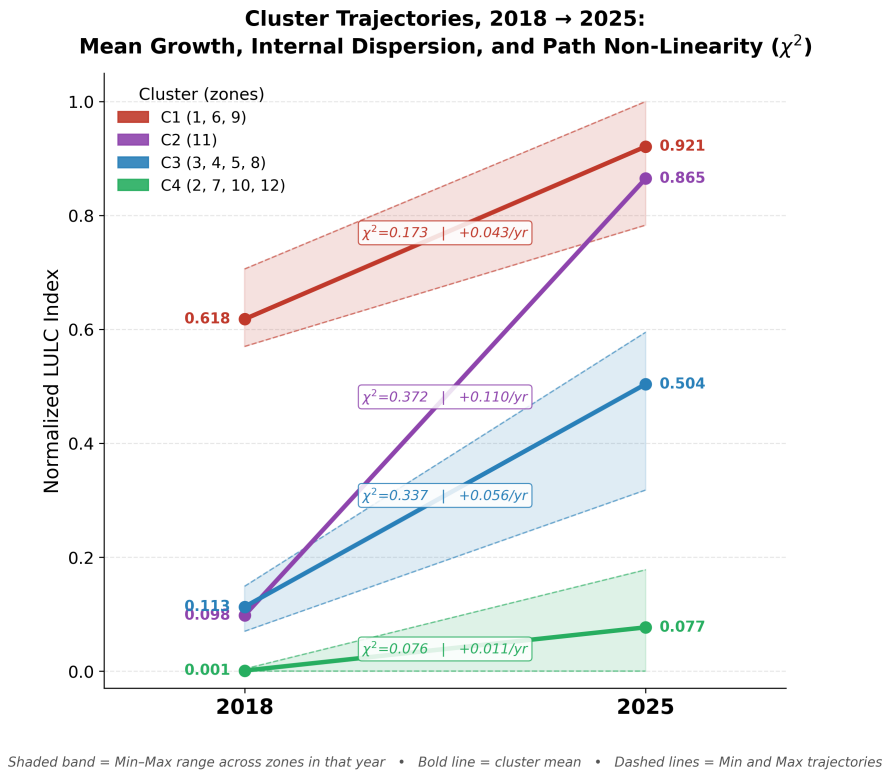


Figure 56: Cluster-level trajectories of the Normalized LULC Dynamics Index (NLDI) from 2018 to 2025. The bold line marks each cluster's mean and its average annual rate of change; the shaded band spans its Min–Max range in each year; and the annotated χ^2 value indicates how far each cluster's actual path deviated from a straight line between its 2018 and 2025 means.

Cluster 3 ((3) Aman Economic Zone, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, and (8) Karnaphuli Dry Dock Special Economic Zone) again shows (3)

Aman Economic Zone lagging the other three, though here the gap opens through sharper, discrete jumps rather than gradual acceleration. Cluster 4 ((2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (10) Kishoreganj Economic Zone, and (12) Cumilla Economic Zone) remains the lowest cluster mean, at both endpoints, of any cluster across all three indices, and includes (7) Shirajganj Economic Zone, the only zone in the entire dataset with a flat 0.000 built-up index in every single year from 2018 to 2025.

6.10 Cross-Index Comparison and Overall Interpretation

Taken together, the three indices tell a consistent story about *which* zones are urbanizing fastest, but they disagree noticeably on *how smoothly* that urbanization proceeds and on the *absolute level* reached by 2025. The four subsections above already walked through each cluster’s numbers across all three measures; the three clustering plots below revisit that same cluster-by-cluster narrative, one index at a time, so that the visual grouping of zones can be read directly against the findings just discussed.

Cluster 1 ((1) Meghna Economic Zone, (6) City Economic Zone, (9) East West Special Economic Zone) tops every index in both years, but its 2025 cluster mean is highest on the Normalized Urbanization Index (NUI) (0.949), intermediate on the Normalized LULC Dynamics Index (NLDI) (0.921), and lowest on the Equally Weighted Core Urbanization Index (ECUI) (0.754), confirming that population and nighttime-lights growth in this core cluster is lagging behind its physical construction footprint.

Cluster 2 ((11) Hossaindi Economic Zone) is the most striking case of index divergence: its net change ranges from 0.4478 under the ECUI to 0.633 under the Normalized Urbanization Index and all the way to 0.767 under the NLDI, with a raw χ^2 of 0.372 on the LULC measure alone over ten times its own χ^2 on the ECUI (0.036). This confirms that Hossaindi’s transformation is real on every measure, but that its volatility is concentrated in the built-up classification itself rather than in population or light-emission data, consistent with discrete construction phases (the 2020–2021 dip, the 2022 turning point) being smoothed out once population and NTL are blended in.

Cluster 3 ((3) Aman Economic Zone, (4) Bay Economic Zone, (5) Meghna Industrial Economic Zone, (8) Karnaphuli Dry Dock Special Economic Zone) shows the widest 2025 Min–Max spread of any cluster on every index (0.219 on the Normalized Urbanization Index (NUI), 0.167 on the ECUI, 0.277 on the NLDI), and (3) Aman Economic Zone is consistently the laggard while (5) Meghna Industrial Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone consistently pull ahead, indicating that the ranking within this cluster is driven by built-up land conversion capacity rather than by which underlying variables a given index emphasizes.

Cluster 4 ((2) Abdul Monem Economic Zone, (7) Shirajganj Economic Zone, (10) Kishoreganj Economic Zone, (12) Cumilla Economic Zone) remains the lowest-scoring cluster on all three indices at both endpoints, and (7) Shirajganj Economic Zone is the only zone in the dataset with a flat 0.000 LULC score across all eight years. Within this cluster, however, the identity of the fastest-growing zone differs by index: (10) Kishoreganj Economic Zone, helped by its comparatively higher surrounding population density, posts the largest net change on the Normalized Urbanization Index and the LULC Index, whereas (12) Cumilla Economic Zone overtakes it on the ECUI, suggesting that Cumilla’s population and nighttime-lights growth is accelerating somewhat faster, relative to its own small base, than its physical built-up expansion alone would indicate.

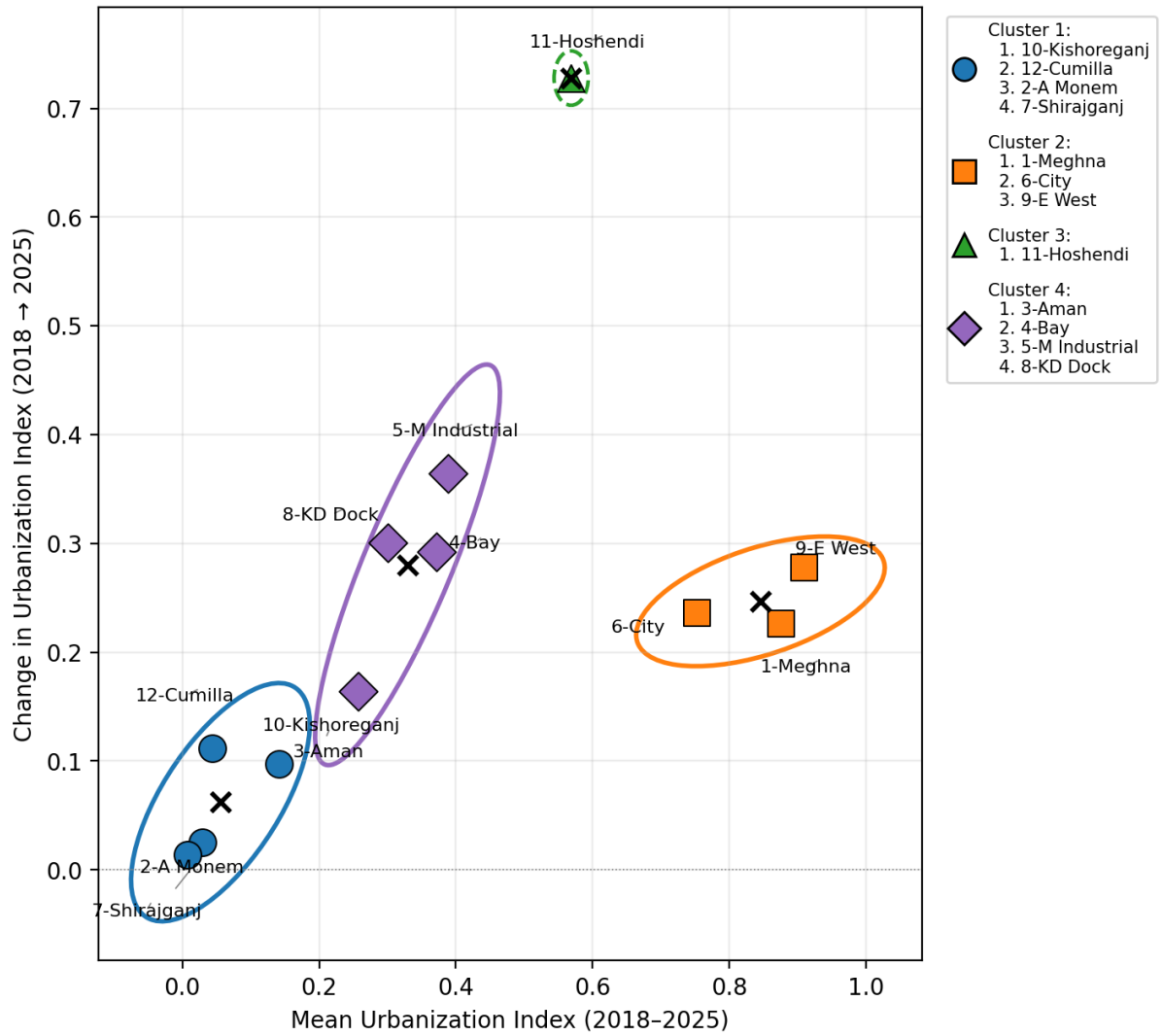


Figure 57: Zone clustering of the Normalized Urbanization Index (NUI) (2018–2025). The horizontal axis shows each zone’s mean normalized urbanization index across the study period; the vertical axis shows the net change in the index between 2018 and 2025. Marker shape and colour together denote cluster membership (K-Means, $k = 4$, fitted on the full eight-year standardized trajectory); the dashed green outline marks the single-zone Cluster 2 ((11) Hossaindi Economic Zone), for which a covariance-based ellipse is undefined.

On this first plot, Cluster 1’s three zones sit farthest right and highest on the vertical axis, reflecting their position as the dataset’s leaders in both mean level and net change. Cluster 2’s single point, marked by the dashed outline, sits apart from every other zone, high on the vertical axis despite a middling horizontal position, visually confirming that Hossaindi’s net change is large even though its average level across the study period is more moderate. Cluster 3’s four zones cluster together in the middle of the plot, spread widely enough along the vertical axis to show (5) Meghna Industrial Economic Zone and (8) Karnaphuli Dry Dock Special Economic Zone pulling above (3) Aman Economic Zone. Cluster 4’s four zones sit lowest and farthest left, tightly grouped near the origin, with only (10) Kishoreganj Economic Zone detaching slightly upward from the other three.

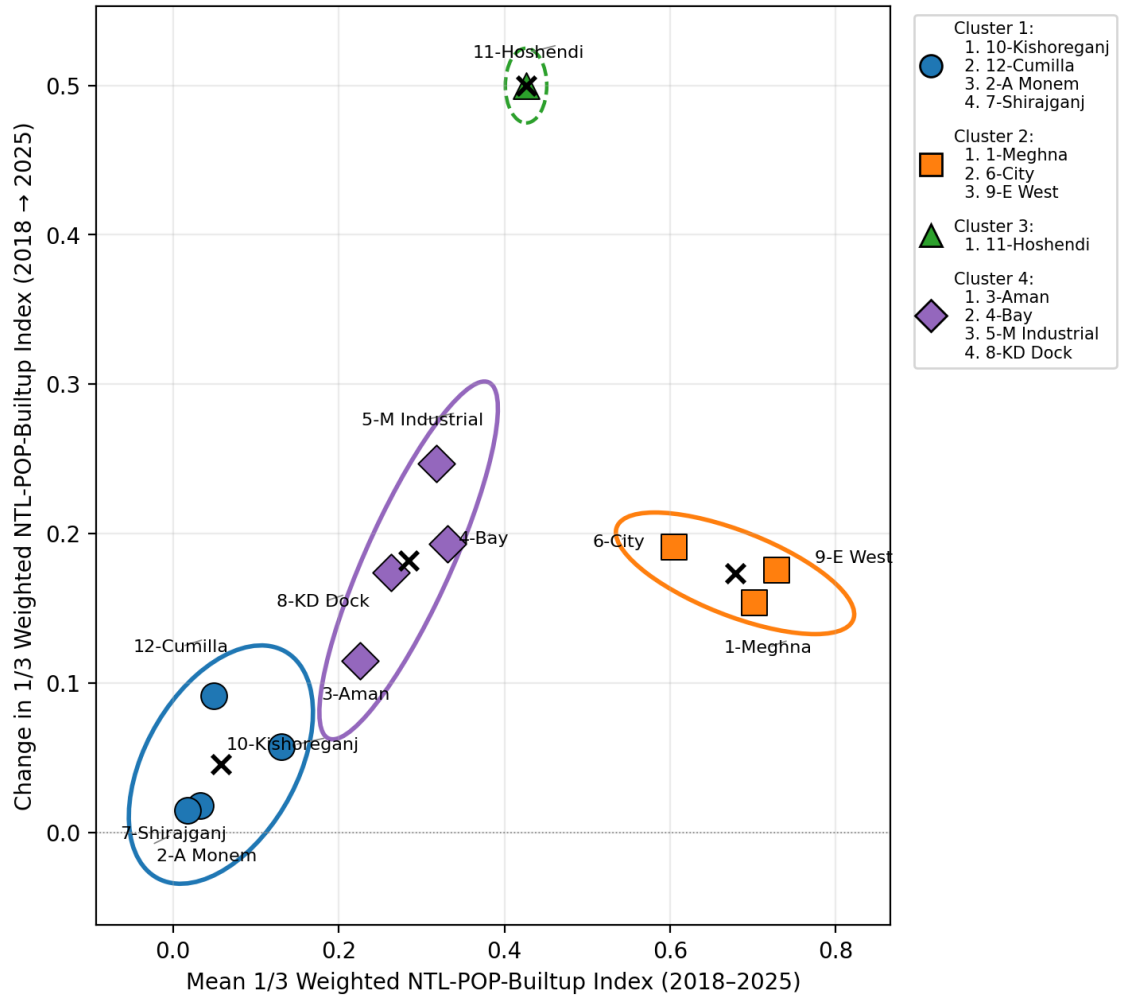


Figure 58: Zone clustering of the Equally Weighted Core Urbanization Index (ECUI) (2018–2025). The horizontal axis shows each zone’s mean index value across the study period; the vertical axis shows the net change in the index between 2018 and 2025. Marker shape and colour together denote cluster membership (K-Means, $k = 4$, fitted on the full eight-year standardized trajectory); the dashed green outline marks the single-zone Cluster 2 ((11) Hossaindi Economic Zone), for which a covariance-based ellipse is undefined.

This second plot compresses the vertical spread of Cluster 1 relative to the first plot, consistent with its lower 2025 mean (0.754) on this index, while its three zones remain the rightmost group overall. Cluster 2’s point moves noticeably lower on the vertical axis than in the previous plot, reflecting its reduced net change (0.448 against 0.633), even though it still stands apart from the other clusters. Cluster 3 again occupies the middle of the plot, its internal spread narrower than on the LULC plot shown next but still wide enough to separate (3) Aman Economic Zone from its three cluster peers. Cluster 4 remains the lowest and leftmost group, though here the point for (12) Cumilla Economic Zone sits slightly higher than (10) Kishoreganj Economic Zone’s, reversing their relative vertical order from the first plot.

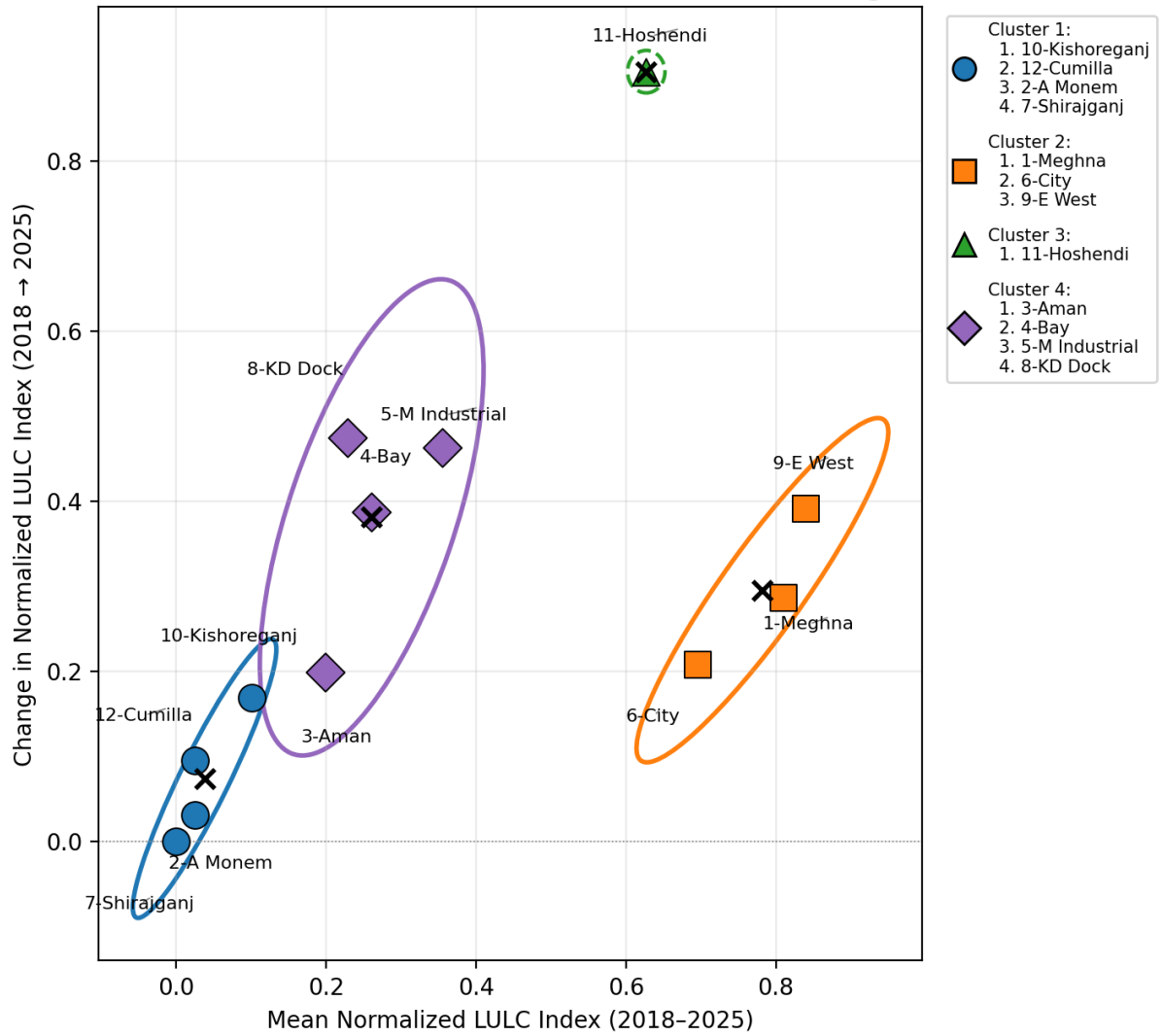


Figure 59: Zone clustering of the Normalized LULC Dynamics Index (NLDI) (2018–2025). The horizontal axis shows each zone’s mean normalized LULC index across the study period; the vertical axis shows the net change in the index between 2018 and 2025. Marker shape and colour together denote cluster membership (K-Means, $k = 4$, fitted on the full eight-year standardized trajectory); the dashed green outline marks the single-zone Cluster 2 ((11) Hossaindi Economic Zone), for which a covariance-based ellipse is undefined.

The third plot shows the most extreme vertical spread of the three, consistent with this index’s larger raw χ^2 values throughout. Cluster 1 again sits rightmost, with its vertical position now the highest of the three plots, matching its highest 2025 mean across the three indices (0.921). Cluster 2’s point rises further still, above every other zone on the vertical axis, reflecting its dataset-leading net change of 0.767. Cluster 3 shows its widest internal vertical spread here, with (8) Karnaphuli Dry Dock Special Economic Zone and (5) Meghna Industrial Economic Zone both detaching clearly above (3) Aman Economic Zone. Cluster 4 remains the lowest group on both axes, its four points clustered near the origin, with (7) Shirajganj Economic Zone’s point sitting exactly at zero net change, the only such point across all three plots.

7. Conclusion and Future Works

7.1 Conclusion

This study developed and applied a multi-source remote-sensing framework to examine the internal development trajectories of twelve Private Economic Zones in Bangladesh over the period 2018–2025. The central analytical principle was to use the exact, manually verified zero-offset footprint of each economic zone as the fixed unit of observation. This distinction is important because the wider buffer zones, intersecting Upazilas, and Upazila Group (UG) Zones were prepared as reusable spatial and data-acquisition infrastructure, whereas the quantitative results reported in this thesis are restricted to the twelve zero-offset economic-zone footprints.

The study integrated three complementary dimensions of development. High-resolution LULC represented physical land transformation through five analytical classes: Farmland, Water, Forest, Built-up, and Meadow. VIIRS nighttime-light data provided a complementary signal associated with artificial illumination and human activity, while WorldPop provided a spatially distributed demographic measure. These datasets were harmonized through a common 100-m analytical framework using dataset-specific aggregation procedures. The resulting annual records were then used to derive the Normalized Urbanization Index (NUI), Equally Weighted Core Urbanization Index (ECUI), and Normalized LULC Dynamics Index (NLDI).

The results show that the twelve economic zones do not follow a single development trajectory. The four observed trajectory clusters identified through the longitudinal index series and $k = 4$ K-Means clustering distinguish zones that begin and remain relatively highly developed, zones that undergo rapid late-stage transformation, zones with intermediate or diverging trajectories, and zones that remain comparatively low throughout the study period. These four analytical clusters are distinct from the five Upazila Group (UG) Zones that were created for spatial acquisition and processing efficiency.

The endpoint index values further demonstrate the heterogeneity of internal development. (1) Meghna Economic Zone, (6) City Economic Zone, and (9) East West Special Economic Zone remain among the highest-scoring zones across the three indices. (11) Hossaindi Economic Zone is the clearest example of rapid transformation, increasing from 0.0979 to 0.8647 on the NLDI and from 0.1527 to 0.6005 on the ECUI between 2018 and 2025, while its NUI increased from 0.1595 to 0.7921. This difference among indices indicates that physical land-cover transformation can occur more rapidly than the corresponding change in demographic and nighttime-light signals.

The lower-development zones also demonstrate why annual trajectories are more informative than a single endpoint value. (7) Shirajganj Economic Zone remains at 0.0000 on the NLDI throughout the study period, whereas (10) Kishoreganj Economic Zone and (12) Cumilla Economic Zone show measurable increases by 2025 despite their low starting positions. The results therefore distinguish between zones that remain persistently low and zones that begin from low baselines but subsequently show measurable development.

Comparison across the three indices further demonstrates that the definition of development matters. The NLDI responds directly to the physical composition of land cover and can therefore show sharper changes when built-up land expands or other classes decline. The ECUI focuses on the three positive anthropogenic signals of built-up land, nighttime lights, and population, and consequently provides a smoother complementary trajectory. The NUI combines these positive signals with the remaining LULC components and therefore captures another dimension of relative urbanization intensity. The three indices are consequently interpreted as complementary measures rather than as interchangeable measures of economic output.

Overall, the study demonstrates that the internal maturation of Private Economic Zones can be monitored systematically using a consistent combination of high-resolution LULC, nighttime lights, and gridded population. The resulting framework provides a spatially explicit baseline for identifying zones with substantial internal build-out, zones undergoing rapid transformation, and zones where physical development remains limited. It also establishes a reusable spatial and computational foundation for future studies of surrounding urbanization and potential spillover.

7.2 Limitations

The findings should be interpreted within several methodological limitations. First, the analysis is restricted to the twelve Private Economic Zones selected during the study design, and the zero-offset boundaries were manually digitized and visually verified. Although this procedure provides a consistent analytical footprint, small positional uncertainties may remain, particularly for smaller zones.

Second, the approximately 2-m optical products used for LULC inference are generated through the Gamma S2DR4 super-resolution workflow from Sentinel-2 observations and therefore should not be interpreted as equivalent to native 2-m commercial imagery. The annual LULC estimates are also subject to uncertainty associated with image quality, reference data, model adaptation, preprocessing, and class separability. Similarly, VIIRS nighttime lights have a substantially coarser native resolution than the 100-m analytical grid, while WorldPop provides modelled gridded population estimates rather than direct population counts for every 100-m cell.

Third, the LULC, NTL, and population variables are indirect indicators of development rather than direct measures of investment, industrial production, employment, or economic output. The three indices are consequently intended as complementary spatial indicators, and their values should not be interpreted as direct measures of economic performance. In addition, the use of Min–Max normalization and equal weighting in the ECUI affects the scale and interpretation of the resulting scores.

Finally, the study is observational and focuses on the exact zero-offset economic-zone footprints. The results therefore identify spatial and temporal associations but do not establish causal effects of economic-zone development, nor do they quantitatively attribute surrounding urbanization or spillover to the zones. These limitations define the appropriate scope of interpretation while providing clear directions for subsequent research.

7.3 Ethical Considerations

This study relies on secondary geospatial and administrative information rather than individual-level primary data. The principal datasets consist of satellite imagery, nighttime-light composites, gridded population estimates, LULC reference information, and economic-

zone boundary information. No personal identifiers, household records, employment records, or individual-level socioeconomic attributes were collected or used.

The population component is represented through spatially aggregated WorldPop estimates rather than individual census records. Results are reported at the level of economic zones and spatial grid cells used for the analysis, and the study does not attempt to identify individual landholders, workers, residents, or households.

The study also avoids attributing observed underdevelopment or rapid development to the behavior of particular individuals. References to highly developed, rapidly transforming, or relatively low-development zones describe spatial patterns observed in the remote-sensing data and do not constitute judgments about individual developers, communities, or landholders.

Because remote-sensing classification can contain errors, the study uses visual inspection and data-quality procedures to reduce the possibility that classification artifacts are interpreted as confirmed land-cover change. The methodological workflow is documented so that the processing can be reproduced and independently examined.

7.4 Impact On The Society

The social relevance of this study lies primarily in its ability to provide an independent spatial basis for monitoring how economic-zone development translates into physical land transformation and associated demographic and nighttime-light patterns. Economic zones are intended to support industrial activity, employment, infrastructure, and wider economic development. At the same time, establishing an economic zone can commit land to an intended industrial use before substantial physical development has actually occurred.

The study therefore provides a mechanism for distinguishing zones that have already undergone substantial internal build-out from zones where the physical transformation of the formal footprint remains limited. This information can support more targeted monitoring by policymakers, planners, and relevant authorities rather than relying only on administrative designation or planned development status.

The social implications should nevertheless be interpreted carefully. Remote sensing can identify spatial patterns but cannot by itself determine whether particular communities benefited from or were adversely affected by economic-zone development. Questions of compensation, employment quality, land acquisition, livelihood change, and access to infrastructure require additional socioeconomic and institutional information. The results should therefore be used as a spatial monitoring layer that complements, rather than replaces, community-level and administrative evidence.

7.4.1 Sustainability Of The Work

A principal sustainability benefit of the framework is its repeatability. The workflow is based largely on openly accessible or regularly updated geospatial data sources, including Sentinel-2, VIIRS nighttime-light observations, and WorldPop. Once the zone boundaries and processing framework have been established, subsequent annual monitoring can be performed without rebuilding the complete spatial framework from the beginning.

The previously prepared 1–5 km buffers, intersecting Upazilas, and five Upazila Group (UG) Zones further improve the sustainability of future processing. These spatial supersets were prepared so that overlapping geographic areas could be acquired and processed efficiently rather than repeatedly downloaded for individual zones. Their retention reduces future duplication of computational effort, storage, processing time, and data-acquisition requirements.

The framework is also transferable. Given a reliable economic-zone boundary, the same processing logic can be applied to additional economic zones or comparable industrial areas. This makes the workflow suitable as a baseline monitoring framework rather than a one-time analysis.

7.4.2 Social and Environmental Effects And Analysis

The environmental relevance of the study arises from observed changes in farmland, water, forest, meadow, and built-up land within the formal economic-zone footprints. Several zones show substantial changes in their land-cover composition, while others remain comparatively stable. Such patterns demonstrate that economic-zone development can involve not only construction of industrial surfaces but also changes in the composition of agricultural and natural land covers.

The findings should not, however, be interpreted as a complete assessment of environmental impact. The present analysis does not directly measure air pollution, water quality, land-surface temperature, biodiversity, greenhouse-gas emissions, or ecosystem services. The LULC, NTL, and population indicators provide spatial evidence of development intensity, while a comprehensive environmental-impact assessment would require additional environmental datasets and field or institutional measurements.

From a social perspective, zones with substantial physical development and stronger population and nighttime-light signals may indicate environments where industrial infrastructure and associated human activity are becoming more established. Conversely, persistent low internal development may indicate that the expected benefits of industrial land allocation have not yet been accompanied by comparable physical build-out. These interpretations should be combined with official investment, employment, infrastructure, and community-level information before policy decisions are made.

7.5 Research Contributions

The research makes the following principal contributions.

1. **A fixed-boundary multi-zone framework.** The study establishes a common zero-offset analytical framework for twelve Private Economic Zones and maintains these spatial units consistently throughout the 2018–2025 longitudinal analysis.
2. **An integrated multi-source development framework.** High-resolution LULC, VIIRS nighttime lights, and gridded population are integrated within a common spatial framework to represent physical, luminous, and demographic dimensions of development.
3. **An annual high-resolution LULC workflow.** Sentinel-2 observations are transformed through the Gamma S2DR4 super-resolution workflow and adapted to the BOLM-based LULC classification framework to produce annual high-resolution LULC information for the study period.
4. **A common 100-m analytical framework.** The study establishes a snapped 100-m master grid and applies dataset-specific procedures to harmonize categorical LULC and continuous NTL and population datasets without treating their different data properties as equivalent.

5. **Three complementary development indices.** The study formulates the Normalized Urbanization Index (NUI), Equally Weighted Core Urbanization Index (ECUI), and Normalized LULC Dynamics Index (NLDI) to distinguish different dimensions of internal economic-zone development.
6. **A longitudinal comparison of twelve Private Economic Zones.** The study identifies distinct development trajectories across the twelve zones and characterizes four observed trajectory clusters derived from the annual index patterns using $k = 4$ K-Means clustering.
7. **A reusable spatial and computational baseline.** The prepared multi-scalar buffers, administrative intersections, Upazila Group (UG) Zones, and processing framework provide an established baseline for future regional and spillover research without requiring the complete spatial data-acquisition process to be rebuilt.

These contributions together provide a reproducible spatial baseline for monitoring the internal maturation of Private Economic Zones in Bangladesh while retaining a clear distinction between observed remote-sensing development signals and direct economic measures.

7.6 Future Plan

Future research can extend the present framework from internal economic-zone development to the wider regional effects of industrialization. The existing 1–5 km buffers, intersecting Upazilas, and Upazila Group (UG) Zones provide a prepared spatial basis for comparing changes inside the economic zones with surrounding LULC, nighttime lights, and population. This would allow potential urban and demographic spillover to be examined without repeating the full spatial-data acquisition and preparation process.

A second direction is to strengthen causal interpretation and validation. Future studies could incorporate suitable control areas or matched comparison locations and apply quasi-experimental approaches to distinguish changes associated with economic-zone development from broader regional trends. Additional high-resolution reference data, field observations, and independent LULC validation samples could also improve uncertainty assessment. Integration of official investment, employment, industrial-unit, infrastructure, and electricity-related information would further allow remote-sensing indicators to be compared with measurable socioeconomic activity.

Finally, the framework can be extended temporally and environmentally. More frequent optical and nighttime-light observations could help identify the timing of construction and operational changes, while variables such as land-surface temperature, vegetation, surface water, flooding, and air quality could be incorporated to investigate environmental consequences. The same framework could also be extended to other economic or industrial zones in Bangladesh and, with appropriate adaptation, to comparable industrial landscapes in other developing-country contexts.

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A. Zero-Offset Annual Analytical Dataset

This appendix documents the quantitative dataset underlying the reported zero-offset analysis of the twelve Private Economic Zones. The final dataset contains 96 annual zone-year records, corresponding to twelve fixed zero-offset economic-zone footprints observed for eight years from 2018 to 2025.

Unlike manually prepared summary tables, the values reported here were generated computationally from the processed raster datasets. The annual LULC, population, and nighttime-lights GeoTIFF products were extracted within the exact zero-offset zone boundaries using Python-based geospatial processing scripts. The extracted values were then combined, calculated, and exported to the final zero-offset CSV. The CSV therefore represents a machine-generated quantitative ledger rather than a manually entered data table.

The appendix provides the principal annual variables in two compact tables to maintain readability on standard A4 portrait pages. The complete 41-field CSV is retained as the accompanying machine-readable dataset.

A.1 Annual LULC and Spatial Variables

Table 14: Annual zero-offset LULC composition and spatial area for the twelve Private Economic Zones, 2018–2025.

Economic zone	Year	Area (km ²)	Farm. (%)	Water	Forest	Built- up (%)	Mead. (%)
(1) Meghna Economic Zone	2018	0.71	4.23	1.41	0.00	67.61	26.76
(1) Meghna Economic Zone	2019	0.71	2.82	1.41	1.41	66.20	28.17
(1) Meghna Economic Zone	2020	0.71	5.63	1.41	0.00	67.61	25.35
(1) Meghna Economic Zone	2021	0.71	5.63	1.41	0.00	80.28	12.68
(1) Meghna Economic Zone	2022	0.71	0.00	0.00	0.00	80.28	19.72
(1) Meghna Economic Zone	2023	0.71	0.00	0.00	0.00	84.51	15.49
(1) Meghna Economic Zone	2024	0.71	0.00	0.00	0.00	95.77	4.23
(1) Meghna Economic Zone	2025	0.71	0.00	0.00	0.00	95.77	4.23
(2) Abdul Monem Economic Zone	2018	1.63	34.97	6.13	0.00	0.00	58.90
(2) Abdul Monem Economic Zone	2019	1.63	31.90	0.61	0.00	2.45	65.03

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Table 14 – continued from previous page

Economic zone	Year	Area (km ²)	Farm. (%)	Water	Forest	Built- up (%)	Mead. (%)
(2) Abdul Monem Economic Zone	2020	1.63	22.70	3.68	0.00	2.45	71.17
(2) Abdul Monem Economic Zone	2021	1.63	23.93	1.23	0.00	2.45	72.39
(2) Abdul Monem Economic Zone	2022	1.63	18.40	0.61	0.00	3.07	77.91
(2) Abdul Monem Economic Zone	2023	1.63	30.67	0.00	0.00	3.07	66.26
(2) Abdul Monem Economic Zone	2024	1.63	26.38	0.00	0.00	3.07	70.55
(2) Abdul Monem Economic Zone	2025	1.63	26.99	0.00	0.00	3.07	69.94
(3) Aman Economic Zone	2018	0.46	78.26	8.70	0.00	10.87	2.17
(3) Aman Economic Zone	2019	0.46	82.61	4.35	0.00	13.04	0.00
(3) Aman Economic Zone	2020	0.46	82.61	4.35	0.00	13.04	0.00
(3) Aman Economic Zone	2021	0.46	78.26	4.35	0.00	17.39	0.00
(3) Aman Economic Zone	2022	0.46	82.61	4.35	0.00	13.04	0.00
(3) Aman Economic Zone	2023	0.46	82.61	0.00	0.00	17.39	0.00
(3) Aman Economic Zone	2024	0.46	56.52	2.17	0.00	41.30	0.00
(3) Aman Economic Zone	2025	0.46	63.04	6.52	0.00	30.43	0.00
(4) Bay Economic Zone	2018	0.21	61.90	14.29	0.00	14.29	9.52
(4) Bay Economic Zone	2019	0.21	57.14	4.76	0.00	19.05	19.05
(4) Bay Economic Zone	2020	0.21	33.33	0.00	0.00	19.05	47.62
(4) Bay Economic Zone	2021	0.21	33.33	4.76	0.00	14.29	47.62
(4) Bay Economic Zone	2022	0.21	33.33	0.00	0.00	14.29	52.38
(4) Bay Economic Zone	2023	0.21	19.05	0.00	0.00	28.57	52.38
(4) Bay Economic Zone	2024	0.21	4.76	4.76	0.00	42.86	47.62
(4) Bay Economic Zone	2025	0.21	0.00	0.00	0.00	52.38	47.62
(5) Meghna Industrial Economic Zone	2018	0.79	29.11	0.00	3.80	11.39	55.70
(5) Meghna Industrial Economic Zone	2019	0.79	29.11	0.00	3.80	15.19	51.90
(5) Meghna Industrial Economic Zone	2020	0.79	21.52	0.00	12.66	15.19	50.63
(5) Meghna Industrial Economic Zone	2021	0.79	18.99	0.00	12.66	17.72	50.63
(5) Meghna Industrial Economic Zone	2022	0.79	5.06	0.00	6.33	54.43	34.18
(5) Meghna Industrial Economic Zone	2023	0.79	5.06	0.00	6.33	54.43	34.18
(5) Meghna Industrial Economic Zone	2024	0.79	5.06	0.00	6.33	54.43	34.18
(5) Meghna Industrial Economic Zone	2025	0.79	2.53	0.00	6.33	56.96	34.18
(6) City Economic Zone	2018	0.44	0.00	2.27	4.55	54.55	38.64
(6) City Economic Zone	2019	0.44	0.00	2.27	2.27	72.73	22.73
(6) City Economic Zone	2020	0.44	0.00	2.27	0.00	59.09	38.64
(6) City Economic Zone	2021	0.44	0.00	2.27	0.00	59.09	38.64
(6) City Economic Zone	2022	0.44	0.00	2.27	0.00	79.55	18.18
(6) City Economic Zone	2023	0.44	0.00	2.27	0.00	72.73	25.00
(6) City Economic Zone	2024	0.44	0.00	2.27	0.00	75.00	22.73
(6) City Economic Zone	2025	0.44	0.00	2.27	0.00	75.00	22.73
(7) Shirajganj Economic Zone	2018	4.86	97.53	0.00	1.85	0.00	0.62
(7) Shirajganj Economic Zone	2019	4.86	97.33	0.00	1.23	0.00	1.44

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Table 14 – continued from previous page

Economic zone	Year	Area (km ²)	Farm. (%)	Water	Forest	Built- up (%)	Mead. (%)
(7) Shirajganj Economic Zone	2020	4.86	96.50	0.00	1.23	0.00	2.26
(7) Shirajganj Economic Zone	2021	4.86	6.17	0.00	1.23	0.00	92.59
(7) Shirajganj Economic Zone	2022	4.86	5.76	0.00	1.65	0.00	92.59
(7) Shirajganj Economic Zone	2023	4.86	5.56	0.00	1.23	0.00	93.21
(7) Shirajganj Economic Zone	2024	4.86	2.88	0.00	1.65	0.00	95.47
(7) Shirajganj Economic Zone	2025	4.86	2.06	0.00	1.23	0.00	96.71
(8) Karnaphuli Dry Dock Special Economic Zone	2018	0.15	0.00	46.67	0.00	6.67	46.67
(8) Karnaphuli Dry Dock Special Economic Zone	2019	0.15	0.00	46.67	0.00	13.33	40.00
(8) Karnaphuli Dry Dock Special Economic Zone	2020	0.15	0.00	20.00	0.00	13.33	66.67
(8) Karnaphuli Dry Dock Special Economic Zone	2021	0.15	0.00	6.67	0.00	13.33	80.00
(8) Karnaphuli Dry Dock Special Economic Zone	2022	0.15	0.00	6.67	0.00	6.67	86.67
(8) Karnaphuli Dry Dock Special Economic Zone	2023	0.15	0.00	6.67	6.67	26.67	60.00
(8) Karnaphuli Dry Dock Special Economic Zone	2024	0.15	0.00	0.00	0.00	46.67	53.33
(8) Karnaphuli Dry Dock Special Economic Zone	2025	0.15	0.00	0.00	0.00	53.33	46.67
(9) East West Special Economic Zone	2018	5.35	14.02	10.65	2.80	55.33	17.20
(9) East West Special Economic Zone	2019	5.35	11.03	4.30	0.75	76.64	7.29
(9) East West Special Economic Zone	2020	5.35	12.52	3.18	0.19	75.14	8.97
(9) East West Special Economic Zone	2021	5.35	1.50	4.11	0.00	94.39	0.00
(9) East West Special Economic Zone	2022	5.35	9.91	1.31	0.00	88.79	0.00
(9) East West Special Economic Zone	2023	5.35	9.16	1.87	0.00	88.97	0.00
(9) East West Special Economic Zone	2024	5.35	8.79	2.62	0.00	88.60	0.00
(9) East West Special Economic Zone	2025	5.35	1.12	4.86	0.00	93.83	0.19
(10) Kishoreganj Economic Zone	2018	0.47	97.87	0.00	0.00	2.13	0.00
(10) Kishoreganj Economic Zone	2019	0.47	80.85	0.00	0.00	19.15	0.00
(10) Kishoreganj Economic Zone	2020	0.47	82.98	0.00	0.00	17.02	0.00
(10) Kishoreganj Economic Zone	2021	0.47	100.00	0.00	0.00	0.00	0.00
(10) Kishoreganj Economic Zone	2022	0.47	100.00	0.00	0.00	0.00	0.00
(10) Kishoreganj Economic Zone	2023	0.47	82.98	0.00	0.00	17.02	0.00

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Economic zone	Year	Area (km ²)	Farm. (%)	Water	Forest	Built- up (%)	Mead. (%)
(10) Kishoreganj Economic Zone	2024	0.47	91.49	0.00	0.00	8.51	0.00
(10) Kishoreganj Economic Zone	2025	0.47	82.98	0.00	0.00	17.02	0.00
(11) Hoshendi Economic Zone	2018	0.64	32.81	7.81	7.81	9.38	42.19
(11) Hoshendi Economic Zone	2019	0.64	43.75	0.00	0.00	56.25	0.00
(11) Hoshendi Economic Zone	2020	0.64	67.19	0.00	0.00	32.81	0.00
(11) Hoshendi Economic Zone	2021	0.64	51.56	0.00	1.56	34.38	12.50
(11) Hoshendi Economic Zone	2022	0.64	25.00	0.00	0.00	73.44	1.56
(11) Hoshendi Economic Zone	2023	0.64	4.69	0.00	0.00	93.75	1.56
(11) Hoshendi Economic Zone	2024	0.64	4.69	0.00	0.00	95.31	0.00
(11) Hoshendi Economic Zone	2025	0.64	15.62	0.00	0.00	82.81	1.56
(12) Cumilla Economic Zone	2018	1.82	96.15	0.00	3.85	0.00	0.00
(12) Cumilla Economic Zone	2019	1.82	34.62	0.00	0.00	0.00	65.38
(12) Cumilla Economic Zone	2020	1.82	34.62	0.00	0.00	0.00	65.38
(12) Cumilla Economic Zone	2021	1.82	34.62	0.00	0.00	0.00	65.38
(12) Cumilla Economic Zone	2022	1.82	0.00	0.00	3.85	0.00	96.15
(12) Cumilla Economic Zone	2023	1.82	0.00	0.00	0.00	3.85	96.15
(12) Cumilla Economic Zone	2024	1.82	0.00	0.00	0.00	6.59	93.41
(12) Cumilla Economic Zone	2025	1.82	0.00	0.00	0.00	9.34	90.66

A.2 Annual NTL, Population, and Development Indices

Table 15: Annual nighttime-light density, population density, and development-index values for the twelve Private Economic Zones, 2018–2025. Index values are reproduced to four decimal places.

Economic zone	Year	NTL/km ²	POP/km ²	NUI	ECUI	NLDI
(1) Meghna Economic Zone	2018	3684.24	6774.90	0.7664	0.6230	0.7059
(1) Meghna Economic Zone	2019	3361.68	6978.94	0.7433	0.6024	0.6912
(1) Meghna Economic Zone	2020	3746.06	7187.81	0.7797	0.6376	0.7059
(1) Meghna Economic Zone	2021	3069.58	7379.87	0.8209	0.6405	0.8382

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Table 15 – continued from previous page

Economic zone	Year	NTL/km ²	POP/km ²	NUI	ECUI	NLDI
(1) Meghna Economic Zone	2022	4848.96	7586.45	0.9321	0.7623	0.8382
(1) Meghna Economic Zone	2023	5192.43	7877.54	0.9852	0.8063	0.8824
(1) Meghna Economic Zone	2024	3866.77	8177.51	0.9815	0.7647	1.0000
(1) Meghna Economic Zone	2025	3935.06	8483.93	0.9927	0.7770	1.0000
(2) Abdul Monem Economic Zone	2018	297.03	759.35	0.0119	0.0224	0.0000
(2) Abdul Monem Economic Zone	2019	302.27	749.73	0.0270	0.0307	0.0256
(2) Abdul Monem Economic Zone	2020	207.81	756.81	0.0215	0.0247	0.0256
(2) Abdul Monem Economic Zone	2021	313.04	765.20	0.0280	0.0318	0.0256
(2) Abdul Monem Economic Zone	2022	296.96	770.94	0.0309	0.0329	0.0320
(2) Abdul Monem Economic Zone	2023	347.62	784.22	0.0342	0.0366	0.0320
(2) Abdul Monem Economic Zone	2024	424.01	800.87	0.0392	0.0420	0.0320
(2) Abdul Monem Economic Zone	2025	390.72	817.28	0.0376	0.0403	0.0320
(3) Aman Economic Zone	2018	600.34	4600.08	0.1858	0.1765	0.1135
(3) Aman Economic Zone	2019	661.23	4735.78	0.2058	0.1912	0.1362
(3) Aman Economic Zone	2020	633.69	4869.81	0.2073	0.1928	0.1362
(3) Aman Economic Zone	2021	783.33	4996.13	0.2457	0.2203	0.1816
(3) Aman Economic Zone	2022	592.42	5131.92	0.2109	0.1968	0.1362
(3) Aman Economic Zone	2023	705.70	5310.45	0.2483	0.2233	0.1816
(3) Aman Economic Zone	2024	794.25	5492.85	0.4035	0.3134	0.4313
(3) Aman Economic Zone	2025	936.29	5678.47	0.3501	0.2912	0.3178
(4) Bay Economic Zone	2018	1392.11	5603.22	0.2773	0.2653	0.1492
(4) Bay Economic Zone	2019	1045.10	5796.92	0.2901	0.2634	0.1989
(4) Bay Economic Zone	2020	1069.69	5996.48	0.2962	0.2701	0.1989
(4) Bay Economic Zone	2021	1409.23	6193.12	0.2921	0.2815	0.1492
(4) Bay Economic Zone	2022	1628.87	6394.73	0.3099	0.3010	0.1492
(4) Bay Economic Zone	2023	2168.22	6639.98	0.4349	0.3902	0.2983
(4) Bay Economic Zone	2024	1784.13	6904.45	0.5050	0.4194	0.4475
(4) Bay Economic Zone	2025	1785.32	7180.44	0.5695	0.4583	0.5469
(5) Meghna Industrial Economic Zone	2018	1054.91	3918.93	0.2003	0.1906	0.1190
(5) Meghna Industrial Economic Zone	2019	1298.45	4024.34	0.2404	0.2219	0.1586
(5) Meghna Industrial Economic Zone	2020	1332.66	4139.50	0.2451	0.2271	0.1586
(5) Meghna Industrial Economic Zone	2021	1374.96	4265.57	0.2660	0.2415	0.1850
(5) Meghna Industrial Economic Zone	2022	1852.13	4397.40	0.5212	0.3985	0.5683
(5) Meghna Industrial Economic Zone	2023	2168.99	4571.31	0.5442	0.4237	0.5683
(5) Meghna Industrial Economic Zone	2024	1757.93	4744.22	0.5236	0.4012	0.5683
(5) Meghna Industrial Economic Zone	2025	2111.28	4921.32	0.5643	0.4373	0.5948
(6) City Economic Zone	2018	2390.17	7069.41	0.6163	0.5023	0.5695

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Table 15 – continued from previous page

Economic zone	Year	NTL/km ²	POP/km ²	NUI	ECUI	NLDI
(6) City Economic Zone	2019	2005.24	7264.81	0.7086	0.5427	0.7594
(6) City Economic Zone	2020	2504.22	7475.78	0.6603	0.5353	0.6170
(6) City Economic Zone	2021	2283.43	7666.73	0.6515	0.5257	0.6170
(6) City Economic Zone	2022	2667.35	7858.60	0.8035	0.6239	0.8305
(6) City Economic Zone	2023	4139.30	8130.29	0.8564	0.7045	0.7594
(6) City Economic Zone	2024	3999.50	8410.81	0.8684	0.7101	0.7831
(6) City Economic Zone	2025	3630.89	8689.15	0.8528	0.6930	0.7831
(7) Shirajganj Economic Zone	2018	113.05	718.76	0.0000	0.0093	0.0000
(7) Shirajganj Economic Zone	2019	310.28	720.87	0.0118	0.0223	0.0000
(7) Shirajganj Economic Zone	2020	184.56	723.04	0.0044	0.0141	0.0000
(7) Shirajganj Economic Zone	2021	245.69	724.96	0.0081	0.0182	0.0000
(7) Shirajganj Economic Zone	2022	208.95	726.76	0.0059	0.0158	0.0000
(7) Shirajganj Economic Zone	2023	219.22	729.57	0.0066	0.0166	0.0000
(7) Shirajganj Economic Zone	2024	307.33	732.27	0.0119	0.0224	0.0000
(7) Shirajganj Economic Zone	2025	333.18	734.86	0.0135	0.0242	0.0000
(8) Karnaphuli Dry Dock Special Economic Zone	2018	1875.25	2772.57	0.1938	0.1994	0.0696
(8) Karnaphuli Dry Dock Special Economic Zone	2019	1677.71	2822.10	0.2238	0.2099	0.1392
(8) Karnaphuli Dry Dock Special Economic Zone	2020	2245.69	2869.56	0.2589	0.2483	0.1392
(8) Karnaphuli Dry Dock Special Economic Zone	2021	1933.02	2911.53	0.2411	0.2289	0.1392
(8) Karnaphuli Dry Dock Special Economic Zone	2022	1752.93	2960.82	0.1909	0.1961	0.0696
(8) Karnaphuli Dry Dock Special Economic Zone	2023	2355.85	3034.27	0.3505	0.3042	0.2784
(8) Karnaphuli Dry Dock Special Economic Zone	2024	1933.96	3103.84	0.4487	0.3450	0.4873
(8) Karnaphuli Dry Dock Special Economic Zone	2025	1995.99	3173.90	0.4946	0.3731	0.5569
(9) East West Special Economic Zone	2018	2186.74	11943.80	0.7225	0.6159	0.5777
(9) East West Special Economic Zone	2019	1870.13	12114.12	0.8373	0.6706	0.8002
(9) East West Special Economic Zone	2020	2101.42	12268.82	0.8456	0.6847	0.7846
(9) East West Special Economic Zone	2021	2258.85	12454.06	0.9766	0.7639	0.9856
(9) East West Special Economic Zone	2022	2218.57	12637.59	0.9443	0.7472	0.9270
(9) East West Special Economic Zone	2023	2547.97	12908.42	0.9714	0.7763	0.9290
(9) East West Special Economic Zone	2024	2566.84	13178.86	0.9766	0.7832	0.9251
(9) East West Special Economic Zone	2025	2320.84	13447.32	1.0000	0.7914	0.9797
(10) Kishoreganj Economic Zone	2018	152.80	3891.10	0.0893	0.1000	0.0044

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Table 15 – continued from previous page

Economic zone	Year	NTL/km ²	POP/km ²	NUI	ECUI	NLDI
(10) Kishoreganj Economic Zone	2019	102.07	3918.83	0.1905	0.1541	0.1999
(10) Kishoreganj Economic Zone	2020	198.38	3946.99	0.1840	0.1540	0.1777
(10) Kishoreganj Economic Zone	2021	164.56	3973.73	0.0789	0.0958	0.0000
(10) Kishoreganj Economic Zone	2022	211.29	4001.66	0.0824	0.0995	0.0000
(10) Kishoreganj Economic Zone	2023	248.41	4041.05	0.1892	0.1597	0.1777
(10) Kishoreganj Economic Zone	2024	184.28	4079.92	0.1344	0.1281	0.0889
(10) Kishoreganj Economic Zone	2025	180.93	4118.85	0.1869	0.1573	0.1777
(11) Hoshendi Economic Zone	2018	871.21	3165.78	0.1595	0.1527	0.0979
(11) Hoshendi Economic Zone	2019	832.61	3193.12	0.4432	0.3071	0.5873
(11) Hoshendi Economic Zone	2020	1394.98	3198.22	0.3343	0.2659	0.3426
(11) Hoshendi Economic Zone	2021	2610.62	3223.00	0.4171	0.3514	0.3589
(11) Hoshendi Economic Zone	2022	2111.38	3249.78	0.6257	0.4496	0.7668
(11) Hoshendi Economic Zone	2023	3456.59	3293.08	0.8308	0.6065	0.9789
(11) Hoshendi Economic Zone	2024	3629.07	3335.42	0.8517	0.6240	0.9952
(11) Hoshendi Economic Zone	2025	3889.96	3375.27	0.7921	0.6005	0.8647
(12) Cumilla Economic Zone	2018	325.29	400.10	0.0053	0.0151	0.0000
(12) Cumilla Economic Zone	2019	360.11	401.90	0.0074	0.0174	0.0000
(12) Cumilla Economic Zone	2020	281.63	380.59	0.0022	0.0118	0.0000
(12) Cumilla Economic Zone	2021	358.86	382.92	0.0069	0.0169	0.0000
(12) Cumilla Economic Zone	2022	469.49	385.46	0.0136	0.0242	0.0000
(12) Cumilla Economic Zone	2023	1439.23	389.59	0.0951	0.1006	0.0402
(12) Cumilla Economic Zone	2024	1348.33	390.41	0.1064	0.1038	0.0688
(12) Cumilla Economic Zone	2025	1246.75	393.90	0.1171	0.1064	0.0975

Note: NUI = Normalized Urbanization Index; ECUI = Equally Weighted Core Urbanization Index; NLDI = Normalized LULC Dynamics Index. All three index values are reproduced from the final zero-offset CSV used for the thesis analysis.

B. Data Dictionary of the Zero-Offset Extraction Dataset

The following tables define all 41 fields in the final zero-offset CSV. The first table describes the spatial and LULC fields; the second covers population, nighttime-light, and index variables. The field names are retained exactly as they appear in the machine-generated CSV so that the appendix can be used for reproducibility and audit purposes.

Table 16: Data dictionary: spatial and LULC fields of the zero-offset annual extraction dataset.

CSV field	Description
Zone_Name	Internal identifier of the zero-offset economic-zone spatial unit.
Year	Annual observation year (2018–2025).
Total_Valid_Pixels	Number of valid analytical raster cells contributing to the annual zero-offset extraction.
Area_sqm	Total valid analytical area in square metres.
Area_sqkm	Total valid analytical area in square kilometres.
Area_acres	Total valid analytical area in acres.
LULC1_FARMLAND_px	Number of analytical cells classified as Farmland.
LULC2_WATER_px	Number of analytical cells classified as Water.
LULC3_FOREST_px	Number of analytical cells classified as Forest.
LULC4_BUILTUP_px	Number of analytical cells classified as Built-up.
LULC5_MEADOW_px	Number of analytical cells classified as Meadow.
LULC1_FARMLAND_sqm	Farmland area in square metres.
LULC1_FARMLAND_pct	Farmland share of the valid zone area, in percent.
LULC2_WATER_sqm	Water area in square metres.
LULC2_WATER_pct	Water share of the valid zone area, in percent.
LULC3_FOREST_sqm	Forest area in square metres.
LULC3_FOREST_pct	Forest share of the valid zone area, in percent.
LULC4_BUILTUP_sqm	Built-up area in square metres.
LULC4_BUILTUP_pct	Built-up share of the valid zone area, in percent.
LULC5_MEADOW_sqm	Meadow area in square metres.
LULC5_MEADOW_pct	Meadow share of the valid zone area, in percent.
LULC_Dominant_Class	LULC class with the largest area share for the annual zero-offset footprint.

Table 17: Data dictionary: population, NTL, and development-index fields of the zero-offset annual extraction dataset.

CSV field	Description
POP_Total_Sum	Aggregate population count summed over the valid extracted population cells.
POP_Mean_Density	Mean population value over valid extracted population cells.
POP_Max_Value	Maximum population value among valid extracted cells.
POP_Min_Value	Minimum population value among valid extracted cells.

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CSV field	Description
NTL_Total_Sum	Aggregate nighttime-light radiance value over valid extracted cells.
NTL_Max_Value	Maximum valid nighttime-light radiance value.
NTL_Min_Value	Minimum valid nighttime-light radiance value.
NTL_Mean_Density	Mean nighttime-light radiance over valid extracted cells.
NTL_per_Capita	Aggregate nighttime-light radiance divided by the corresponding aggregate population count.
NTL_to_POP_Mean_Ratio	Ratio of mean nighttime-light density to mean population density.
NTL_per_SqKm	Nighttime-light radiance density per square kilometre.
POP_per_SqKm	Population density per square kilometre.
NTL_Norm(per_sqm)	Min–max normalized NTL density used as an input to the composite indices.
POP_Norm(per_sqm)	Min–max normalized population density used as an input to the composite indices.
Urbanization_Index	Raw urbanization score before final min–max normalization.
Normalized_Urbanization_index	Normalized Urbanization Index (NUI).
_1_3_weigthed_ntl_pop_builtup	Equally Weighted Core Urbanization Index (ECUI), with equal one-third weights.
LULC_index	Raw LULC transformation score before final normalization.
normalized_LULC_index	Normalized LULC Dynamics Index (NLDI).

C. Supplementary Data and Reproducibility Materials

The final zero-offset CSV is the machine-readable quantitative ledger for the reported zone-level analysis. It was generated through Python-based extraction and calculation from the annual LULC, population, and nighttime-lights raster products after spatial masking and alignment to the exact zero-offset economic-zone boundaries. The dataset was organized by **Zone_Name** and **Year**; extracted LULC areas and proportions, population statistics, NTL statistics, density measures, and the three development indices were then consolidated into the final records.

The appendix tables are a human-readable representation of the principal variables. The accompanying CSV preserves the complete field set and numerical precision used by the computational workflow. No values in the CSV were manually entered for the thesis tables; the reported tables reproduce the computed output of the extraction and metric-calculation workflow.