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Quantifying urban ecological imbalance through Green–Grey Space Coordination analysis in rapidly urbanising Gautam Buddha Nagar, India

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Research Article

Keywords: Green–Grey Space Coordination Index (GGSCI), Land Use Transition, Urban Ecology, Sustainable Urban Planning

Posted Date: November 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11570877/v1

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Additional Declarations: No competing interests reported.

Quantifying urban ecological imbalance through Green–Grey Space Coordination analysis in rapidly urbanising Gautam Buddha Nagar, India

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Abstract

Rapid urbanisation has led to a significant transformation in the spatial layout and biological composition of peri-urban landscapes in the National Capital Region (NCR) of India. Gautam Buddha Nagar district is one of the fastest-growing metropolitan regions of the NCR. Massive land transformation has taken place in the region due to industrialisation, infrastructural

development, residential expansion, and transportation growth. The present study analyses spatio-temporal dynamics of Land Use / Land Cover (LULC), landscape modification, and Green – Grey Space Coordination Index (GGSCI) in Gautam Buddha Nagar district between 1991 and 2025 by Remote Sensing and Geographic Information System (GIS) techniques. Multi-temporal satellite images were classified into five key Land Use Land Cover (LULC) groups, including natural vegetation, agriculture, built-up, bareland and water. Transition matrix analysis and alluvial visualisation were used to evaluate directional land-cover transitions of land-cover categories across different temporal periods. Furthermore, a fishnet-based GGSCI framework using 500 m grid cells was developed to evaluate the spatial relationship between ecological green spaces and urban grey spaces. The results reveal rapid expansion of built-up and transitional landscapes accompanied by a continuous decline in agricultural and ecological land-cover components. The major land transformation pathway identified was the conversion of agricultural land to built-up land, demonstrating the corridor-oriented nature of urban expansion in the district. The GGSCI analysis also indicates strong regional variation of the ecological-urban balance, with more urbanised areas showing dominant grey-space concentration, while peripheral regions maintain relatively greater ecological continuity. The findings reveal that the green-grey spatial structure of Gautam Buddha Nagar district has been substantially altered by infrastructure-driven urbanisation, which has resulted in greater ecological strain and landscape fragmentation. The integrated framework of LULC classification, transition matrix analysis, alluvial visualisation, and GGSCI assessment provides a comprehensive framework for assessing long-term urban ecological transformation and promoting sustainable land-use planning in rapidly urbanising metropolitan regions.

Keywords: Green–Grey Space Coordination Index (GGSCI); Land Use Transition; Urban Ecology; Sustainable Urban Planning

1 Introduction

The process of urbanisation has greatly altered the regional landscape structure, ecological composition, and spatial layout in metropolitan regions around the world and especially in the fast-developing countries of Asia. The ongoing extension of urban built-up areas due to

industrialisation, transportation infrastructure, economic concentration, and population growth has hastened the conversion of natural and agricultural landscapes into impervious surfaces and artificial grey infrastructure (Karen C. Seto M. F., 2011; Christopher Bren d'Amour, 2017). The rapid horizontal expansion of urban areas has altered ecological processes, changing ecological processes, hydrological systems and land resource dynamics, and put immense pressure on environmental sustainability and regional ecological resilience. Contemporary urban growth rarely occurs compactly and homogeneously; instead, they are growing in a fragmented, corridor-based, and spatially heterogeneous manner that constantly changes the interaction between the ecological and the built environments (H. S. Sudhira, 2008; Vikrant M S, 2019). Such transformations are particularly pronounced in peri-urban areas where urban and rural landscapes are in dynamic interaction and are extremely susceptible to infrastructure-led land conversion processes (Karen C. Seto B. G., 2012; Chi Chen, 2019).

Over the last few decades, India has witnessed one of the fastest rates of urbanisation internationally, especially in metropolitan areas connected to economic corridors and huge urban agglomerations. Among these regions, the National Capital Region (NCR) represents one of the fastest-growing metropolitan regions in India. Rapid infrastructure development, industrialisation, and population concentration have resulted in significant changes to the landscape (Narain, 2009; Carol Upadhya, 2021). The district of Gautam Buddha Nagar, including Noida, Greater Noida, Dadri and Jewar, is one of the fastest urbanising areas in northern India. The planned townships, industrial corridors, expressways, metro connectivity, logistics infrastructure, and institutional developments have accelerated the conversion of agricultural land, vegetation, and open ecological spaces into urban built-up surfaces (Rai, 2012; Priyadarshini J. Shetty, 2010). Consequently, the district has experienced significant modification in the design of the regional landscape, its ecological structure, and environmental circumstances over time.

Changes in Land Use/Land Cover (LULC) have become a significant problem in urban environmental research, since changes in the structure of land cover directly influence ecological resilience, groundwater recharge, urban climate, biodiversity, and ecosystem services. Ecological landscapes, including agriculture, natural vegetation and water bodies, are significant in preserving the environmental quality, carbon sequestration, hydrological regulation, and ecological continuity. However, the rapid urban expansion usually replaces these biological components with impervious grey infrastructure, including buildings,

transportation networks, industrial regions, and transitory barren land (Chi Chen, 2019; Yuan Bo, 2024). The increasing dominance of grey surfaces leads to a series of environmental disruptions, including ecological fragmentation, decreased infiltration of groundwater, urban heat island effects, habitat degradation, and declining environmental sustainability (Xingliang Guan, 2018; Vincenzo Giannico, 2022). Therefore, understanding the dynamic relationship between urban expansion and ecological transformation has become more and more vital to promote sustainable urban development and environmental resilience.

Remote Sensing and Geographic Information Systems (GIS) approaches provide an effective framework to monitor long-term urban growth and assess spatio-temporal landscape modification. Multi-temporal satellite imagery enables the detection, classification, and measurement of land-use patterns at various phases of urbanisation . Landsat-based analyses, machine learning classification approaches and transition matrix methods have been widely used to study urban expansion and ecological transformation at regional and metropolitan scales (Mariana Belgiu, 2016; Martin Herold, 2003; Xiaoping Liu, 2018; David P. Roy, 2014). The transition matrix and alluvial visualisation techniques also provide detailed insights into the magnitude, direction, and continuity of land transformation processes, allowing for the identification of dominant land conversion trajectories in rapidly urbanising environments (Pontus Olofsson, 2014; Marta Sapena, 2021).

Recently, increasing attention has been directed toward understanding the dynamic link between urban grey areas and ecological green spaces in quickly altering urban systems. Urban green spaces generally include crops and water bodies that serve ecological functions and deliver environmental benefits, whereas grey spaces comprise built-up surfaces and barren land coupled with impermeable infrastructure and human activities . The interplay of these spatial components has a significant effect on ecological sustainability, environmental quality, urban resilience, and the adaptive capacity of metropolitan ecosystems (Chi Chen, 2019; Vincenzo Giannico, 2022). In the areas with accelerated urbanisation, the imbalance between green space and grey space increases the ecological pressure and reduces the stability of urban ecological systems.

To quantify the interaction between ecological and built settings, the Green–Grey Space Coordination Index (GGSCI) has recently emerged as an important framework to examine the relative balance between green and grey spatial components . Previous research mainly employed concentric buffer-based methodologies to examine urban ecological dynamics and

green-grey spatial interactions. However, buffer-based methods tend to overgeneralize limited spatial variability and fail to appropriately capture ecological heterogeneity in fragmented peri-urban areas undergoing fast infrastructure-driven urbanisation . Therefore, fine-scale spatial techniques are necessary to better characterise localised ecological-urban interactions and to identify ecological stress zones linked to urban growth processes.

To overcome these limitations, the present study offers a fishnet-based GGSCI framework with 500 m grid cells to analyse the spatial ecological balance of Gautam Buddha Nagar district. Fishnet-based research gives a more detailed picture of localised green–grey interactions compared to standard buffer-based methodologies and enables the identification of micro-level spatial heterogeneity associated with infrastructure-led urban expansion. Furthermore, the combination of long-term LULC analysis, transition matrix analysis, alluvial visualization and fishnet-based GGSCI evaluation provides a robust framework for analysing urban ecological transformation and spatial trade-offs in rapidly developing metropolitan areas .

Although several studies have investigated urban growth and land transformation in the NCR region. But there is a lack of comprehensive studies on long-term LULC dynamics, land transition pathways, alluvial visualisation, and fine-scale green–grey spatial coordination for the Gautam Buddha Nagar district. Moreover, the ecological ramifications of increasing infrastructure-driven urbanisation have not been thoroughly explored with spatially explicit ecological coordination indicators (Rohan D. Simkin, 2022; United Nations General Assembly, 2023). Therefore, this study aims to investigate the spatio-temporal dynamics of land change and ecological balance in Gautam Buddha Nagar district from 1991 to 2025 by Remote Sensing and GIS methodologies.

The specific objectives of this study are (1) to analyse the spatio-temporal dynamics of Land Use/Land Cover (LULC) in the Gautam Buddha Nagar district from 1991 to 2025, (2) to measure the changes in green and grey spaces with respect to urban expansion, (3) to evaluate land transformation processes through transition matrix analysis, (4) to visualize multi-temporal land transitions through alluvial diagrams, (5) to measure the ecological–urban spatial balance through a 500 m fishnet-based Green–Grey Space Coordination Index (GGSCI), and (6) to study the ecological implications of rapid urbanization and provide scientific insights for sustainable urban planning. The findings of this study advance the understanding of urban ecological changes in fast-growing metropolitan areas and provide scientific support for evidence-based approaches for sustainable urban development. In addition, the study is

consistent with the Sustainable Development Goal (SDG) 11, which calls for sustainable cities and communities and SDG 15, which aims at conserving terrestrial ecosystems and ecological balance in urbanising landscapes (United Nations General Assembly, 2015; United Nations General Assembly, 2023).

2 Study Area

Gautam Buddha Nagar district is situated in the western part of Uttar Pradesh, India, and forms a vital component of the National Capital Region (NCR). The district lies between approximately 28°13′ N to 28°53′ N latitude and 77°17′ E to 77°55′ E longitude and covers an area of nearly 1,442 km². It is bounded by the state of Haryana along the western margin by the Yamuna River, while Delhi and Ghaziabad districts lie to the north and northeast, respectively, and Bulandshahr district forms the southern and eastern boundary of the region. Owing to its strategic proximity to the national capital, the district has emerged as one of the fastest-growing urban and industrial regions in northern India. Administratively, the district comprises the major urban centres of Noida, Greater Noida, Dadri, and Jewar, along with numerous peri-urban and rural settlements . Since the establishment of Noida and Greater Noida as planned urban townships, the district has experienced rapid spatial and socioeconomic transformation driven by industrialisation, residential expansion, transportation infrastructure development, and increasing population concentration (Rai, 2012; Priyadarshini J. Shetty, 2010). The process of urban expansion has been further accelerated by large-scale infrastructure projects, including the Noida–Greater Noida Expressway, Yamuna Expressway, metro corridors, industrial development zones, and logistics infrastructure, which have collectively intensified urban sprawl and landscape transformation across the district . Consequently, extensive agricultural land, open spaces, and ecological landscapes have gradually been converted into built-up surfaces and transitional urban land-use categories. Figure 1 illustrates the geographical extent and spatial location of the study area.

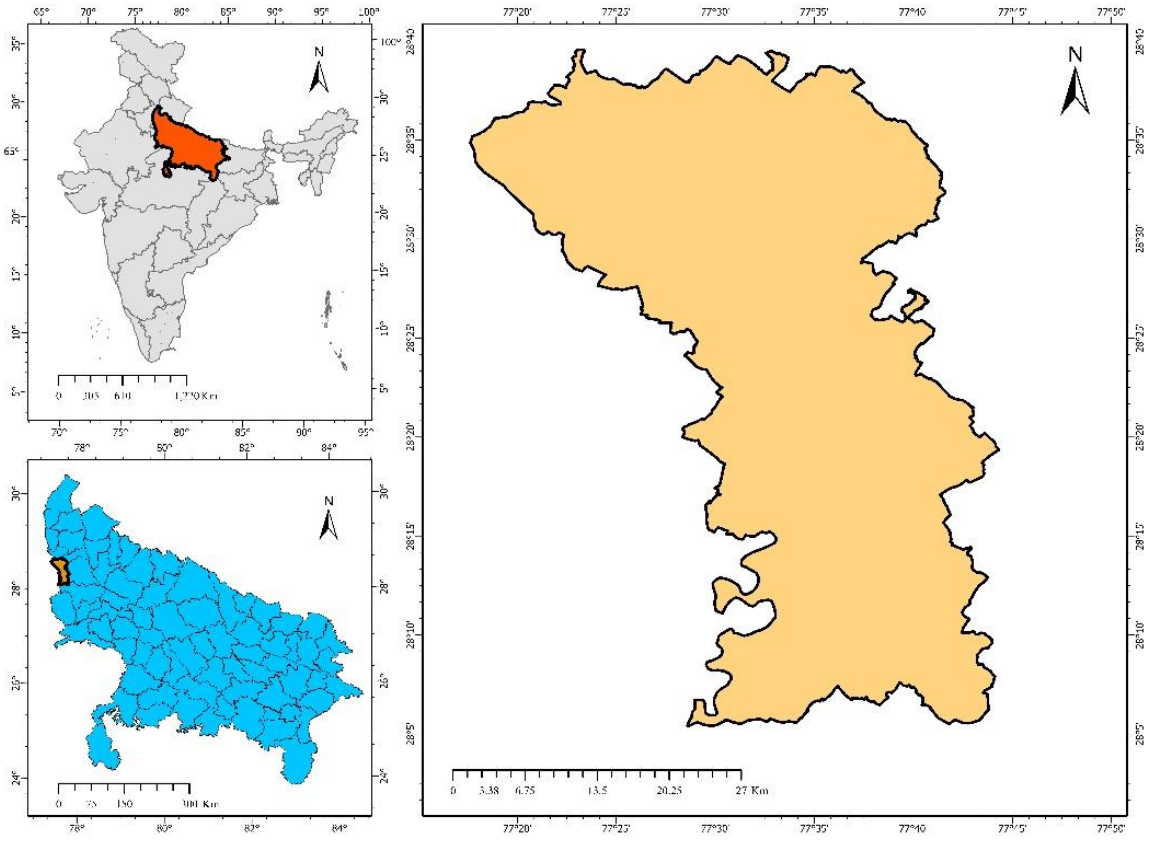


Figure 1: Study Area: Gautam Buddha Nagar

Physiographically, Gautam Buddha Nagar district is located within the Indo-Gangetic alluvial plain and is characterised by relatively flat topography and fertile alluvial soils. The Yamuna River, which forms the western boundary of the district, plays a vital role in regional hydrological processes and groundwater recharge, although localised flooding is frequently observed in low-lying areas during periods of intense monsoonal rainfall (Central Ground Water Board (CGWB), 2022; Ankit Jain, 2020). Historically, agriculture has been the dominant land-use activity across the region; however, rapid infrastructure-led urbanisation has continuously transformed agricultural landscapes and ecological spaces into impervious urban surfaces. The district experiences a sub-tropical semi-arid climate characterised by hot summers, seasonal monsoonal rainfall, and cool winters. The coexistence of rapidly expanding urban infrastructure, peri-urban transitional landscapes, agricultural land, and remnant ecological spaces makes Gautam Buddha Nagar district an important case for investigating long-term Land Use/Land Cover (LULC) dynamics, landscape transformation, and green–grey spatial interactions within rapidly urbanising metropolitan environments (Narain, 2009; Carol Upadhya, 2021).

3 Data and Methodology

3.1 Data Source

The present study utilised multi-temporal satellite imagery, administrative boundary datasets, and derived spatial layers to investigate the spatio-temporal dynamics of Land Use/Land Cover (LULC), landscape transformation, and Green–Grey Space Coordination Index (GGSCI) in Gautam Buddha Nagar district from 1991 to 2025. Multi-temporal Landsat imagery was acquired from the United States Geological Survey (USGS) Earth Explorer platform for the years 1991, 2001, 2011, 2021, and 2025. Depending on data availability for the corresponding years, Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8–9 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) datasets were employed. To ensure temporal consistency and minimize the influence of seasonal spectral variability, cloud-free or minimal cloud-cover scenes acquired during the winter season (January–February) were selected for analysis . The Landsat datasets, with a spatial resolution of 30 m, provide a reliable and consistent platform for long-term regional-scale LULC monitoring and urban growth assessment ; . The geospatial datasets utilised in the study are summarised in Table 1. Minor variations in acquisition dates were necessary due to the availability of cloud-free imagery; however, all scenes fall within the same seasonal window, thereby ensuring inter-annual comparability and minimising phenological variation in land-cover classification.

Administrative boundary data for Gautam Buddha Nagar district were obtained from Survey of India (SOI) geospatial datasets and were utilised for clipping, spatial extraction, and standardisation of all raster layers. The district boundary falls within SOI toposheet series 53H/6, 53H/7, 53H/10, and 53H/11 at 1:50,000 scale. In addition, high-resolution imagery from Google Earth Pro and historical image archives were employed to support training sample generation, visual interpretation, and classification validation during the accuracy assessment stage . The integration of multi-source geospatial datasets improved thematic consistency and enhanced the reliability of the classified outputs ; .

The LULC classification scheme adopted in the study consisted of five major land-cover categories, namely natural vegetation, agriculture, built-up, bareland, and water. These classes were selected to effectively represent the dominant landscape characteristics and urban transformation processes occurring within the district . Following classification, the LULC categories were further reorganized into a binary green–grey spatial framework for ecological–

urban assessment. Green space comprised natural vegetation, agricultural land, and water bodies, representing ecologically functional landscapes, whereas grey space included built-up and bareland categories associated with impervious and anthropogenic surfaces. This reclassification provided the basis for the computation and spatial interpretation of the Green–Grey Space Coordination Index (GGSCI), which has increasingly been applied in recent studies examining urban ecological balance and spatial sustainability (Xi Wang, 2025; Tianyu Zhou, 2023).

Table 1: Geospatial Inputs Used for Long-Term Monitoring of Land System Transformation in Gautam Buddha Nagar

Type	Data	Date	Source
Satellite Imagery	Landsat 4–5 TM Collection 2 Level 2	09 January 1991 16 January 2011	USGS Earth Explorer
	Landsat 7 ETM+ Collection 2 Level 2	28 January 2001	USGS Earth Explorer
	Landsat 8–9 OLI/TIRS Collection 2 Level 2	28 February 2021 30 January 2025	USGS Earth Explorer
Administrative Boundaries	Survey of India (SOI) shapefiles for India, Uttar Pradesh, and Gautam Buddha Nagar	—	Survey of India (SOI)
Topographic Data	SOI Toposheet Series 53H/6, 53H/7, 53H/10, and 53H/11 (Scale 1:50,000)	—	Survey of India (SOI)

To ensure spatial consistency among datasets acquired from different sensors and years, all raster layers were geometrically corrected, projected to a common coordinate system, and resampled to a uniform spatial resolution of 30 m. The processed datasets were subsequently utilized for LULC classification, transition matrix analysis, alluvial visualization, and fishnet-based GGSCI assessment to evaluate long-term urban ecological transformation within Gautam Buddha Nagar district.

3.2 Methodology

3.2.1 Image pre-processing

The present study utilized multi-temporal satellite imagery, administrative boundary datasets, and derived spatial layers to analyse the spatio-temporal dynamics of Land Use/Land Cover

(LULC), landscape transformation, and the Green–Grey Space Coordination Index (GGSCI) in Gautam Buddha Nagar district from 1991 to 2025. Multi-temporal Landsat imagery for the years 1991, 2001, 2011, 2021, and 2025 was acquired from the United States Geological Survey (USGS) Earth Explorer platform. Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8–9 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) datasets were used according to data availability for the corresponding years. To ensure temporal consistency and minimize the influence of seasonal spectral variability, cloud-free or minimum cloud-cover images acquired during the winter season (January–February) were selected for analysis . The Landsat datasets, with a spatial resolution of 30 m, provide a reliable and consistent framework for long-term regional-scale LULC monitoring and urban expansion assessment ; . Minor differences in acquisition dates were unavoidable to obtain cloud-free imagery; however, all scenes fall within the same seasonal window, thereby ensuring inter-annual comparability and reducing phenological inconsistencies in land-cover classification. The geospatial datasets used in this study are summarised in Table 1.

Administrative boundary data for Gautam Buddha Nagar district were obtained from the Survey of India (SOI) geospatial database and were used for clipping, spatial extraction, and standardisation of all raster datasets. The study area is covered by SOI toposheet series 53H/6, 53H/7, 53H/10, and 53H/11 at a scale of 1:50,000. In addition, high-resolution imagery from Google Earth Pro and historical image archives was utilised to support visual interpretation, training sample generation, and classification validation during the accuracy assessment stage . The integration of multi-source geospatial datasets improved the thematic consistency and reliability of the classified outputs and enhanced the overall accuracy of the spatial analysis (Karen C. Seto M. F., 2011; Pontus Olofsson, 2014).

The study adopted five primary land-cover categories for the LULC classification scheme, namely natural vegetation, agricultural land, built-up area, bareland, and water bodies. These categories were selected to represent the dominant landscape characteristics and major urban transformation processes occurring within the district . Following classification, the LULC classes were further reorganised into a binary green–grey spatial framework for ecological–urban assessment. Within this framework, green space was defined as natural vegetation, agricultural land, and water bodies that provide ecological functions and biologically productive landscape characteristics. In contrast, grey space comprised built-up and bareland

categories associated with impervious surfaces, artificial infrastructure, and anthropogenic land transformation processes. This reclassification formed the basis for the calculation and spatial interpretation of the Green–Grey Space Coordination Index (GGSCI), which has increasingly been applied in recent studies related to urban ecological balance, spatial sustainability, and green–grey interaction dynamics (Xi Wang, 2025; Tianyu Zhou, 2023).

To ensure spatial consistency among datasets derived from different sensors and acquisition periods, all raster layers were geometrically corrected, projected into a common coordinate system, and resampled to a uniform spatial resolution of 30 m. The standardised datasets were subsequently used for LULC classification, transition matrix analysis, alluvial visualisation, and fishnet-based GGSCI assessment to evaluate long-term urban ecological transformation and spatial trade-offs in Gautam Buddha Nagar district.

3.2.2 Accuracy Assessment

To verify the reliability, consistency, and thematic robustness of the classification results for all the research years, a rigorous validation approach was employed to test the correctness of the classified Land Use/Land Cover (LULC) maps. Independent validation samples were generated using a systematic random sampling strategy following standard remote sensing validation protocols . The reference samples for the accuracy assessment were created separately from the training datasets used for the Random Forest classification to maintain the statistical independence of model calibration and validation .

The total number of validation points in the datasets varied slightly due to differences in class distribution and spatial heterogeneity across various years. This sampling framework reduced classification bias and increased the reliability of the confusion matrices and associated statistical measures . Validation reference information was mostly taken from high-resolution Google Earth Pro images, historical picture archives, and supplementary geospatial datasets. For recent years, high-resolution satellite imagery available through Google Earth Pro has provided detailed visual interpretation of land-cover categories. However, because high-resolution imagery was not consistently available for the earlier study periods, additional reference support was obtained from Survey of India (SOI) topographical maps, stable geomorphological features, transportation networks, river systems, and long-established settlement patterns.

The classification performance and thematic consistency of the LULC maps were evaluated independently for each study year through the construction of confusion matrices. Standard accuracy assessment metrics, including Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and the Kappa coefficient, were computed from these remote sensing accuracy evaluation methodologies ; ; . Overall Accuracy was calculated as the proportion of correctly classified samples relative to the total number of validation points. Producer's Accuracy and User's Accuracy were used to evaluate omission and commission errors for individual land-cover classes, respectively, while the Kappa coefficient was employed to assess the level of agreement between the classified outputs and reference datasets beyond random chance.

The accuracy assessment results showed the high thematic reliability and classification consistency of all temporal datasets, which confirmed the suitability of classified maps for subsequent transition matrix analysis, alluvial visualisation, and Green–Grey Space Coordination Index (GGSCI) assessment. The strong classification performance also indicates the efficiency of the Random Forest classifier for long-term LULC mapping in heterogeneous and fast urbanising peri-urban areas .

3.2.3 Transition Matrix and Visualisation

Pixel-level transition analysis was performed for five-time intervals of 1991–2001, 2001–2011, 2011–2021, 2021–2025, and the entire period from 1991 to 2025 to study the dynamics of landscape modification in Gautam Buddha Nagar district. The classified Land Use/Land Cover (LULC) maps for each time period were cross-tabulated by applying a cell-by-cell comparison approach to measure the directional conversion of land across the five primary land-cover categories . The result was transition matrices for all potential transformations between classes that took place between two successive study sessions .

The transition matrix approach is a comprehensive evaluation of both the size and direction of landscape modification. The method provided a deeper insight into the processes of urban expansion, agricultural land conversion, ecological decline, and the emergence of transitional barren landscapes associated with infrastructure development, through analysing the conversion pathways among individual LULC categories (Hashem Dadashpoor, 2019; Marta Sapena, 2021). Furthermore, the technique provided an opportunity to identify dominant land

change trajectories, especially the conversion of agricultural and vegetated landscapes to built-up and bareland surfaces in the context of fast urbanisation.

In addition to the transition matrix analysis, alluvial diagrams were created to graphically illustrate the sequential flow and continuity of land-cover modification throughout multiple temporal eras . The alluvial framework was derived from the cross-tabulated transition datasets and shows the relative fraction of source and destination land-cover types across time. Unlike traditional graphical methods, which tend to become visually complicated in multi-temporal investigations . The diagrams clearly show the cumulative process of landscape modification and the main types of ecological conversion and urban sprawl within the area.

Transition matrix analysis combined with alluvial visualisation provided a comprehensive framework to examine long-term processes of land transformation and spatial restructuring associated with rapid infrastructure-led urban growth and peri-urban spatial restructuring (Christopher Bren d'Amour, 2017; Karen C. Seto, B. G., 2012). This combination technique also helped to detect important urbanisation trends, ecological transformation patterns, and landscape conversion trajectories during the study period.

3.2.4 Green–Grey Spatial Framework and Green–Grey Space Coordination Index (GGSCI)

The classified Land Use/Land Cover (LULC) datasets were reclassified into a green–grey binary framework to assess the changing link between biological landscapes and developed environments based on the conceptual approach presented by Xi Wang (2025). The five original LULC categories were grouped into two functional spatial classes: green space, comprising natural vegetation, agricultural land, and water bodies, and grey space, consisting of built-up and bareland categories. This simplified framework was used to evaluate the proportional balance between ecological landscapes and urban infrastructure, which has increasingly become an important indicator of urban ecological sustainability, environmental quality, and spatial resilience ; .

The bareland in the research region mostly comprises transitional land surfaces linked with active construction, land excavation, unoccupied plots, expanding infrastructure and damaged peri-urban landscapes ; ; . Although these surfaces are not permanently urbanised, they

represent the active anthropogenic transformation and contribute to the increased land surface temperature, runoff generation, ecological fragmentation, and environmental degradation ; ; . Consequently, bareland was incorporated within the grey-space category to represent the spatial influence of infrastructure-led urbanisation and transitional urban growth processes more accurately.

The green–grey binary recategorization enabled the simplification of complex land-cover dynamics into an ecological–urban assessment framework suitable for analysing long-term spatial transformation patterns. Furthermore, the approach facilitated the quantification of ecological decline, urban expansion intensity, and the changing proportional relationship between environmentally functional landscapes and impervious anthropogenic surfaces across Gautam Buddha Nagar district.

In the present study, green space was defined as the combined area of natural vegetation, agricultural land, and water bodies, whereas grey space comprised built-up and bareland categories. The calculation of green and grey spaces is expressed as (eq. 1 and eq. 2):

$$S_{green} = S_{vegetation} + S_{agriculture} + S_{water} \quad \text{(Eq. 1)}$$

$$S_{grey} = S_{builtup} + S_{bareland} \quad \text{(Eq. 2)}$$

Where, S_{green} represents the total area of ecologically functional green space, and S_{grey} represents the total area of grey space associated with anthropogenic and impervious surfaces.

To capture localised spatial heterogeneity in green–grey interactions across Gautam Buddha Nagar district, a 500 m fishnet grid framework was employed. Compared with generalised concentric buffer approaches, the fishnet-based framework provides a finer spatial representation of ecological imbalance, transitional urbanisation zones, and heterogeneous urban expansion patterns at the micro-spatial level.

The GGSCI was calculated using the equation (eq. 3):

$$GGSCI = \frac{\Delta S_{green}}{\Delta S_{grey}} = \frac{\left(S_{green,t} - S_{green,t-1}\right)}{\left(S_{grey,t} - S_{grey,t-1}\right)} \quad \text{(Eq. 3)}$$

where $S_{green,t}$ and $S_{green,t-1}$ represent green-space area at two different temporal periods, while $S_{grey,t}$ and $S_{grey,t-1}$ represent the grey-space area during the corresponding periods. The GGSCI values indicate the proportional relationship between ecological growth and grey infrastructure expansion. The index evaluates relative ecological–urban balance rather than absolute land-cover extent, thereby enabling assessment of localised ecological restructuring associated with urban expansion.

To further examine temporal ecological transformation, the change in GGSCI between different study years was calculated as (eq. 4):

$$\Delta GGSCI = GGSCI_{t2} - GGSCI_{t1} \quad \text{(Eq. 4)}$$

where $GGSCI_{t1}$ represents the GGSCI value for the earlier period and $GGSCI_{t2}$ represents the GGSCI value for the later period. Positive values indicate improvement in green–grey coordination, while negative values represent increasing ecological imbalance resulting from accelerated grey infrastructure expansion and declining ecological continuity.

To normalise temporal variations across unequal study intervals, the Annual GGSCI Rate was calculated using (eq. 5):

$$Annual\ GGSCI\ Rate = \frac{GGSCI_{t2} - GGSCI_{t1}}{t2 - t1} \quad \text{(Eq. 5)}$$

This indicator represents the annual rate of change in ecological–urban balance and facilitates the identification of areas experiencing rapid environmental stress, ecological degradation, or relatively balanced spatial development. The integration of fishnet-based GGSCI analysis with multi-temporal LULC assessment further enabled a comprehensive evaluation of localized ecological transformation and urban spatial restructuring across Gautam Buddha Nagar district.

4 Results

4.1 LULC Classification

The Land Use/Land Cover (LULC) classification results reveal substantial landscape transformation in Gautam Buddha Nagar district between 1991 and 2025, primarily driven by rapid urbanisation, infrastructure expansion, and increasing anthropogenic activities (Table 2). The classified maps indicate a continuous increase in built-up and transitional bareland surfaces throughout the study period, whereas agricultural land and natural vegetation experienced a

substantial decline (Fig. 2a–e). These changes indicate a continuous transition from mainly rural and ecological landscapes toward progressively urbanised environments dominated by non-permeable and artificial surfaces. Although agriculture remained the dominant land-use class during the study period, its area declined markedly from 1140.34 km² in 1991 to 565.84 km² in 2025 (Table 2), accounting for nearly a 50 % reduction in agricultural land. The reduction is attributed to the growing conversion of agricultural land into urban infrastructure, residential townships, transit corridors, and industrial zones connected with the rapid expansion of the National Capital Region (NCR). Simultaneously, natural vegetation also exhibited a persistent declining trend, decreasing from 116.51 km² in 1991 to 65.03 km² in 2025 (Table 2), indicating increasing ecological fragmentation and progressive reduction of vegetated landscapes within the district.

However, the built-up area increased substantially over the research period, from 169.87 km2 in 1991 to 596.99 km2 in 2025 (Table 2). The increase in built-up areas reflects the intensive urban development taking place in Noida, Greater Noida, industrial corridors, transit infrastructure, and large-scale residential and commercial projects. The pattern of urban expansion in space also reveals that the corridor-oriented urban development is focused along the main expressways and infrastructural networks, as shown in Figure 2(a–e). Bareland exhibited the most pronounced proportional increase, particularly after 2011, increasing from only 0.72 km² in 1991 to 198.71 km² in 2025 (Table 2). The substantial increase in bareland primarily represents active construction zones, exposed surfaces, land excavation sites, and transitional urban landscapes associated with ongoing infrastructure development and peri-urban transformation processes. The emergence and expansion of these disturbed surfaces further indicate the intensity of recent urbanisation activities within the district (Fig. 2(a–e)). Water bodies showed relatively fewer changes during the study period, ranging from 9.37 to 15.43 km 2 (Table 2). Although the overall extent of water bodies remained relatively stable compared with other land-cover categories, localised reductions and fragmentation were observed in several peri-urban regions due to urban encroachment and land transformation processes.

Table 2: Multi-Decadal Land Use and Land Cover Area (in Sq. Km) for Gautam Buddha Nagar (1991–2025)

LULC Classes	1991	2001	2011	2021	2025
Natural Vegetation	116.51	110.75	91.71	97.62	65.03

Water	14.56	12.83	9.37	14.28	15.43
Bare land	0.72	0.43	2.45	54.51	198.71
Agriculture	1140.34	1077.75	918.41	733.54	565.84
Built-up	169.87	240.24	420.06	542.05	596.99
Total	**1442**	**1442**	**1442**	**1442**	**1442**

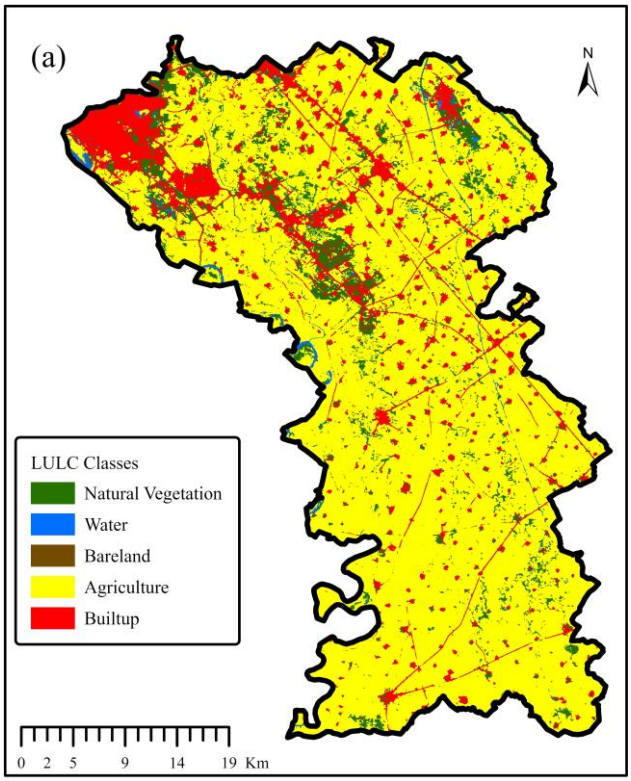


Figure 2 (a): Multi-Decadal Land Use and Land Cover Evolution in Gautam Buddha Nagar, 1991

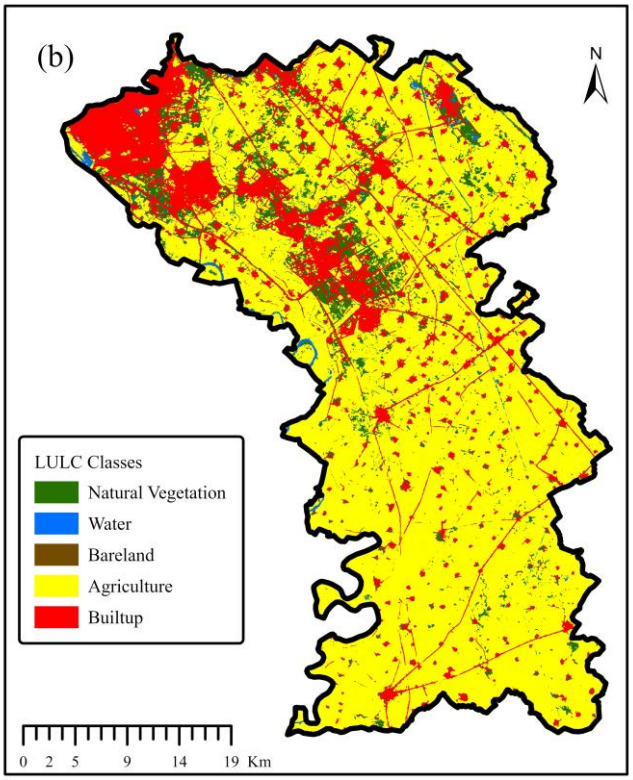


Figure 2 (b): Multi-Decadal Land Use and Land Cover Evolution in Gautam Buddha Nagar, 2001

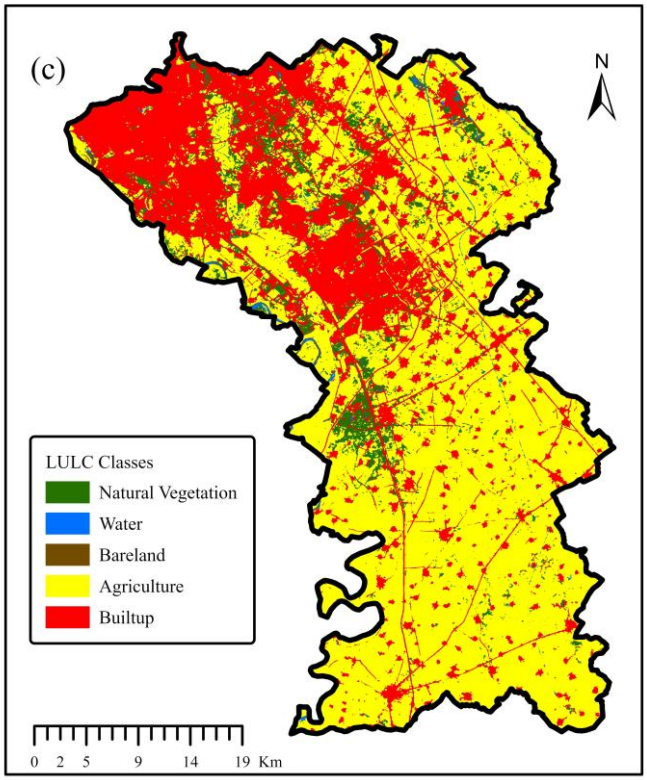


Figure 2 (c): Multi-Decadal Land Use and Land Cover Evolution in Gautam Buddha Nagar, 2011

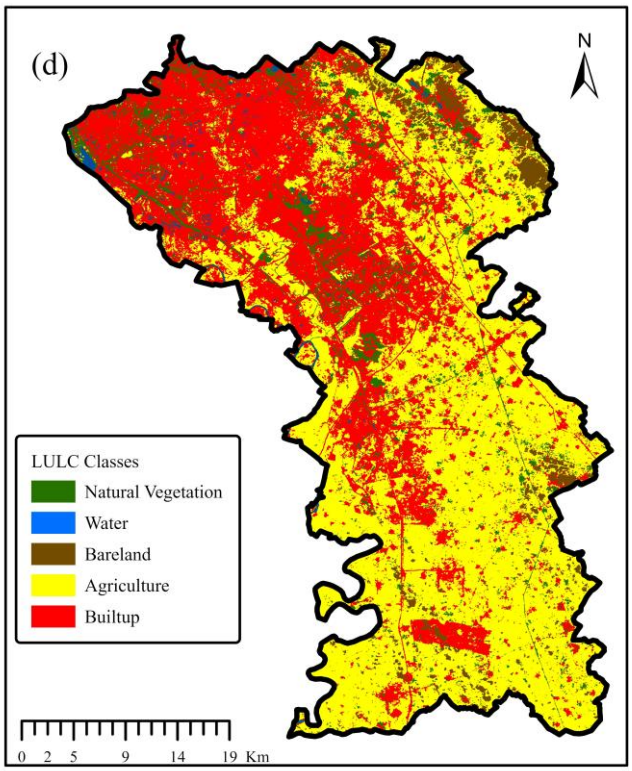


Figure 2 (d): Multi-Decadal Land Use and Land Cover Evolution in Gautam Buddha Nagar, 2021

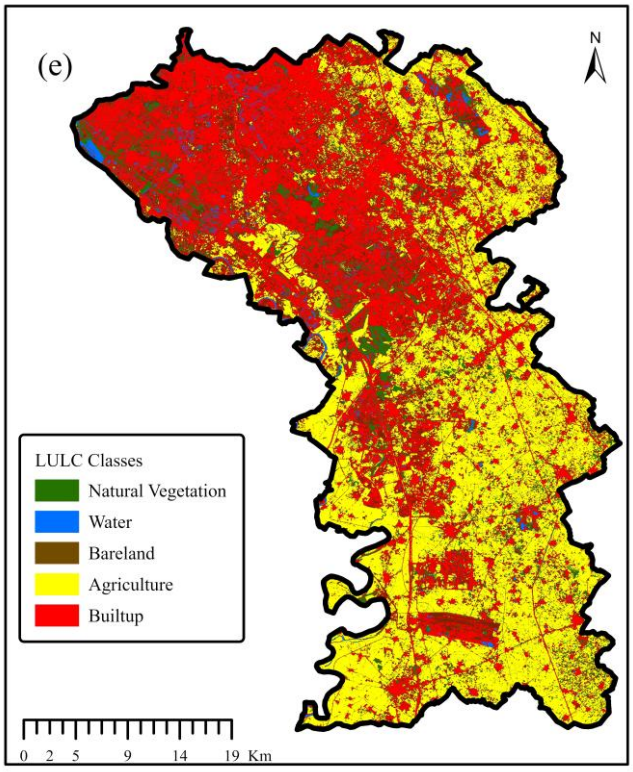


Figure 2 (e): Multi-Decadal Land Use and Land Cover Evolution in Gautam Buddha Nagar, 2025

Overall, the LULC classification results demonstrate a clear transition from predominantly agricultural and ecological landscapes toward increasingly urbanised and impervious surfaces, highlighting the rapid pace of landscape restructuring and ecological transformation in Gautam Buddha Nagar district during the past three decades. The results also show that infrastructure-led urbanisation has significantly changed the regional spatial pattern and aggravated the ecological pressure in the fast-growing metropolitan area.

4.2 Accuracy Assessment

The accuracy assessment results indicate that the classified Land Use/Land Cover (LULC) maps achieved high thematic reliability and classification consistency across all study years (Table 3). The Random Forest classifier demonstrated strong agreement between the classified outputs and reference datasets, confirming the suitability of the generated LULC maps for subsequent transition matrix analysis, alluvial visualisation, and Green–Grey Space Coordination Index (GGSCI) assessment. The Overall Accuracy (OA) values ranged from 92.95% in 1991 to 95.38% in 2001, while the remaining study years also maintained classification accuracies above 90%, indicating stable and consistent classification performance across the multi-temporal datasets. Similarly, the Kappa coefficient values varied between 0.91 and 0.94, reflecting strong agreement between classified outputs and reference data beyond random classification (Table 3). These results demonstrate the effectiveness of the Random Forest algorithm for long-term LULC mapping within heterogeneous and rapidly urbanising peri-urban environments.

Among the individual land-cover categories, built-up, agriculture, and water classes generally exhibited comparatively higher Producer's Accuracy (PA) and User's Accuracy (UA) owing to their relatively distinct spectral and spatial characteristics. In contrast, limited confusion was observed between bareland and built-up surfaces within rapidly transforming peri-urban regions because exposed soil surfaces, construction zones, and newly developing urban areas often exhibit similar spectral responses. Minor classification uncertainty was also observed along fragmented vegetation boundaries and transitional urban landscapes characterised by mixed land-cover conditions. The 1991 classification achieved an Overall Accuracy of 92.95 % with a Kappa coefficient of 0.9119, whereas the 2001 classification produced the highest Overall Accuracy of 95.38 % and a Kappa coefficient of 0.9422 (Table 3). The remaining temporal datasets similarly demonstrated high classification performance, indicating strong thematic consistency throughout the study period.

Table 3: Accuracy Assessment of LULC Classifications for Gautam Buddha Nagar (1991–2025)

Year	Accuracy Parameter	LULC Classes					Overall Accuracy	Overall Kappa
		Vegetation	Water	Barren land	Agriculture	Built-up		
1991	**Reference Total**	102	101	107	98	103	0.9295	0.9119
	Classified Total	101	102	105	98	105		
	Correctly Classified	94	96	97	91	97		
	User's Accuracy	0.9216	0.9505	0.9065	0.9286	0.9417		
	Producer's Accuracy	0.9307	0.9412	0.9238	0.9286	0.9238		
2001	**Reference Total**	102	103	104	101	109	0.9538	0.9422
	Classified Total	102	106	103	102	106		
	Correctly Classified	98	100	97	97	103		
	User's Accuracy	0.9608	0.9709	0.9327	0.9604	0.9450		
	Producer's Accuracy	0.9608	0.9434	0.9417	0.9510	0.9717		
2011	**Reference Total**	102	96	101	103	107	0.9489	0.9361
	Classified Total	102	98	99	103	107		
	Correctly Classified	96	93	95	97	102		
	User's Accuracy	0.9412	0.9688	0.9406	0.9417	0.9533		
	Producer's Accuracy	0.9412	0.9490	0.9596	0.9417	0.9533		
2021	**Reference Total**	105	99	112	101	102	0.9615	0.9518
	Classified Total	105	98	112	101	103		
	Correctly Classified	100	95	108	97	99		
	User's Accuracy	0.9524	0.9596	0.9643	0.9604	0.9706		
	Producer's Accuracy	0.9524	0.9694	0.9643	0.9604	0.9612		
2025	**Reference Total**	104	103	105	113	110	0.9794	0.9743
	Classified Total	103	104	105	113	110		
	Correctly Classified	101	101	103	111	108		
	User's Accuracy	0.9712	0.9806	0.9810	0.9823	0.9818		
	Producer's Accuracy	0.9806	0.9712	0.9810	0.9823	0.9818		

Overall, the consistently high accuracy values confirm the robustness and reliability of the Random Forest classifier for multi-temporal LULC assessment in Gautam Buddha Nagar district. The strong classification performance further ensures the suitability of the classified datasets for evaluating long-term urban expansion, landscape transformation, and ecological–urban interactions within the rapidly urbanising metropolitan environment.

4.3 Transition Matrix

The transition matrix analysis demonstrates a continuing and increasing trend of landscape change in Gautam Buddha Nagar district with a slow change of agricultural and biological landscapes into built-up and transitional urban surfaces (Figure 8). The results show that the conversion of agriculture to built-up is the dominant and most persistent pathway of land transformation during the study period, reflecting the rapid spatial expansion of Noida, Greater Noida, industrial corridors, transportation infrastructure, and peri-urban settlements.

The alluvial diagrams in Figure 3–6 depict the progressive movement of land-cover transitions across various temporal intervals. Between 1991 and 2001, over 92.5 km² of agricultural land was changed to built-up area. This is the first phase of planned urbanisation and expansion of infrastructure in the district. This conversion was enhanced during 2001–2011, when about 127.8 km² of agricultural land was converted to built-up surfaces, matching the increasing industry, residential township growth, and expressway-oriented development. The farmland-to-built-up transition further increased to over 141.7 km 2 between 2011 and 2021, showing an accelerated urban sprawl and expansion of peri-urban infrastructure networks. The biggest transition occurred in 2021-2025, with an area of 164.7 km2 of rural land turned into built-up area, showing the ongoing intensity of infrastructure-led urban expansion. During all studied periods, built-up land showed steady increase, while agricultural land saw the highest net loss, demonstrating its significant contribution to the regional urbanization processes. Natural vegetation also experienced a continuous decrease over time, notably during the latter phases of urban expansion, suggesting an increasing ecological fragmentation and decreasing ecological continuity across peri-urban environments. Although the net area of water bodies changed relatively little, the transition matrices showed a considerable gross exchange of water-related classes between various periods. Transitions are not ultimate net changes, but overall land-cover exchanges, and so are indicative of localized hydrological dynamics and landscape reshaping processes. After 2011, the bareland has significantly increased from only 0.72 km2 in 1991 to 198.71 km2 in 2025. The rise is mainly caused by construction, land

excavation, exposed surfaces, vacant plots, and transitional landscapes related to infrastructure and real-estate development. The fast increase in bareland further emphasizes the dynamic nature of peri-urban transition and continuous land preparation procedures in quickly urbanizing regions.

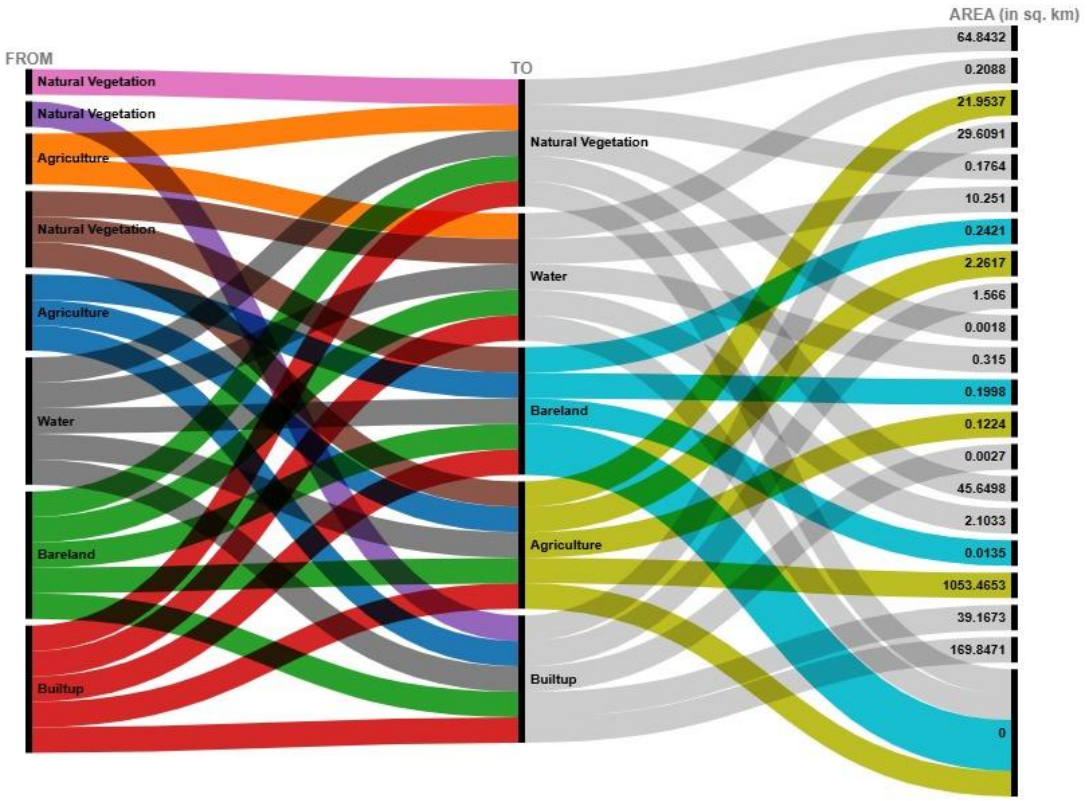


Figure 3: Alluvial diagram illustrating the changes in land cover from 1991 to 2001.

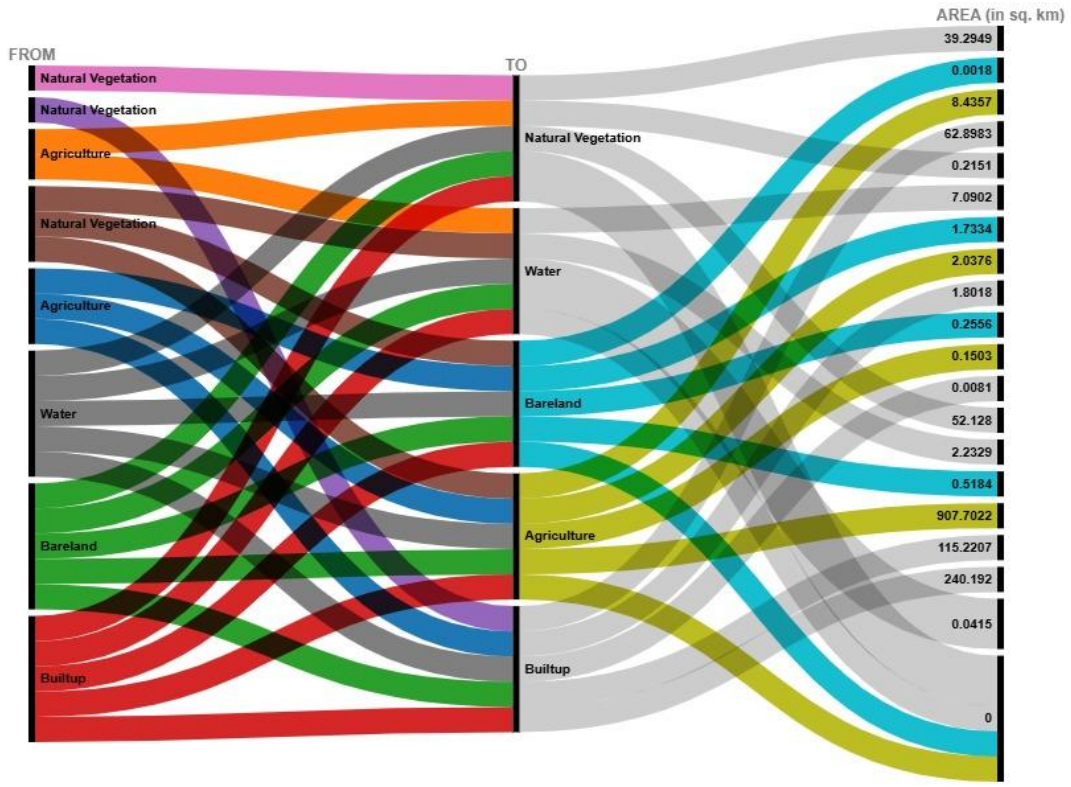


Figure 4: Alluvial diagram illustrating the changes in land cover from 2001 to 2011.

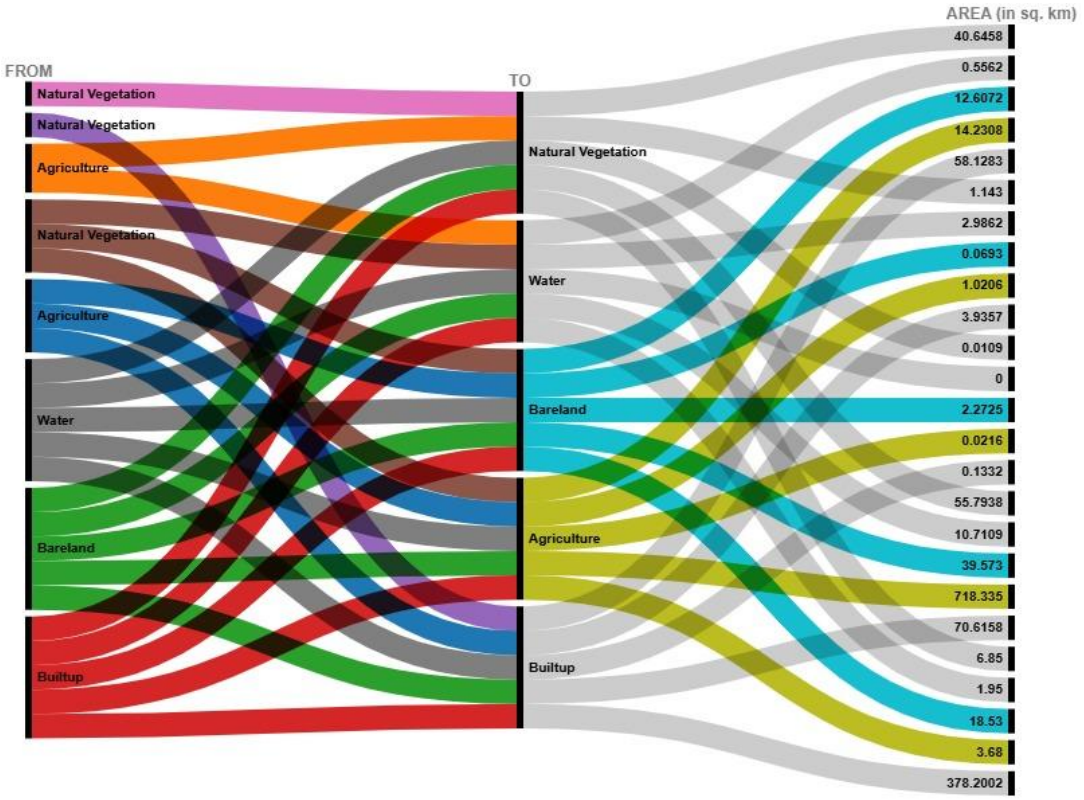


Figure 5: Alluvial diagram illustrating the changes in land cover from 2011 to 2021.

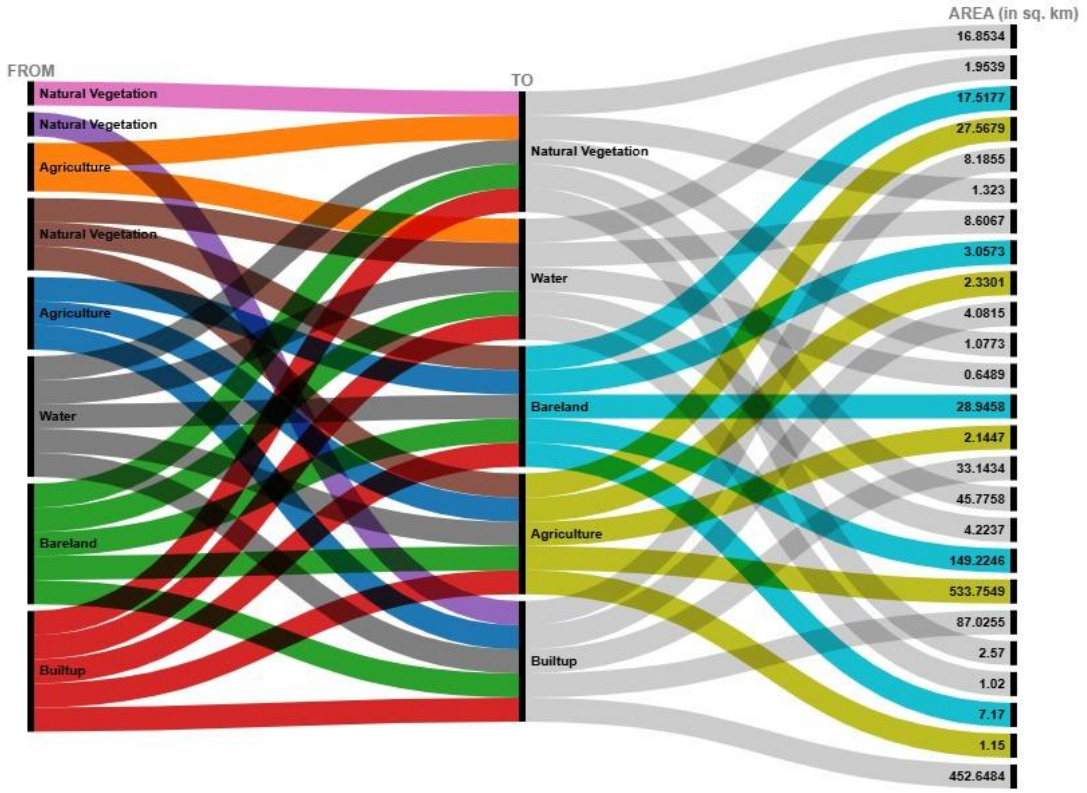


Figure 6: Alluvial diagram illustrating the changes in land cover from 2021 to 2025.

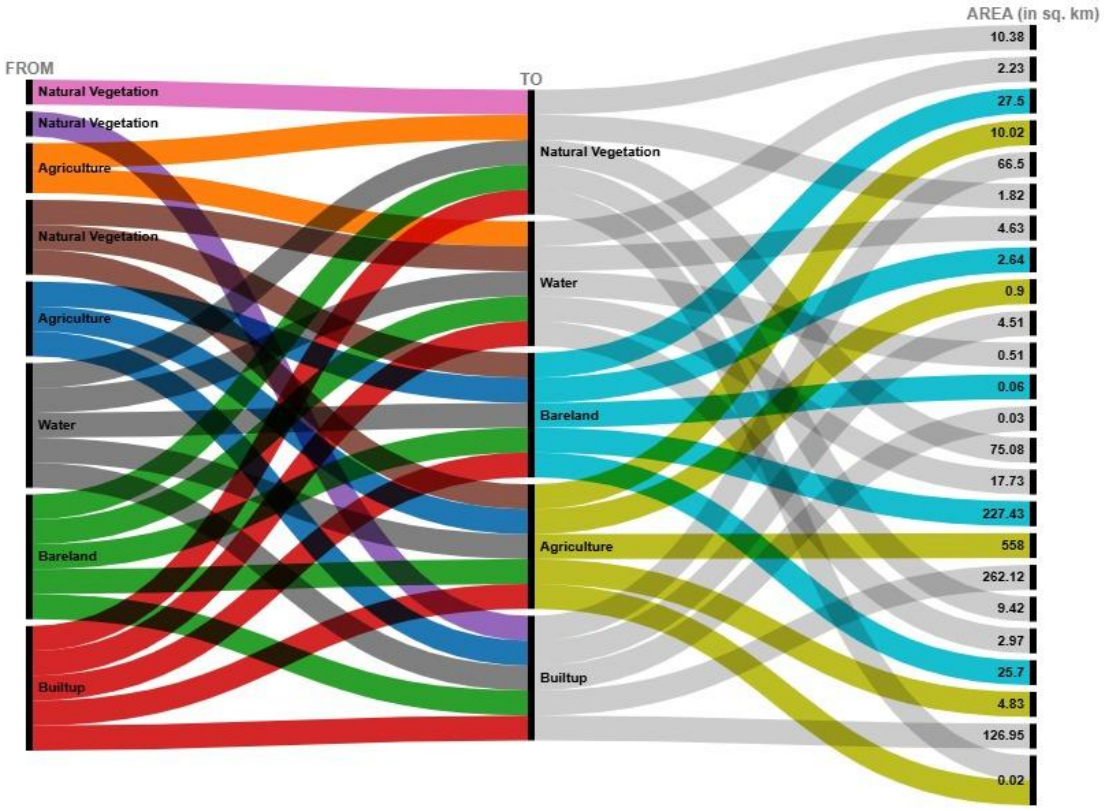


Figure 7: Trajectory of land system change over the decades, illustrating LULC transitions from 1991 to 2025 using an integrated Alluvial diagram.

Alluvial diagrams in Figure 3–7 provide additional illustration of the continuity, amplitude, and directional flow of multi-temporal land alterations between different research periods. From the diagrams, agricultural land has always been the biggest contributor to built-up expansion. The simultaneous rises in bareland show transitional stages of urban development and active processes of construction. In addition, the conversion of natural vegetation to agricultural land reflects the outer spread of agriculture and the intensification of ecological pressure on the remaining natural landscapes ; .

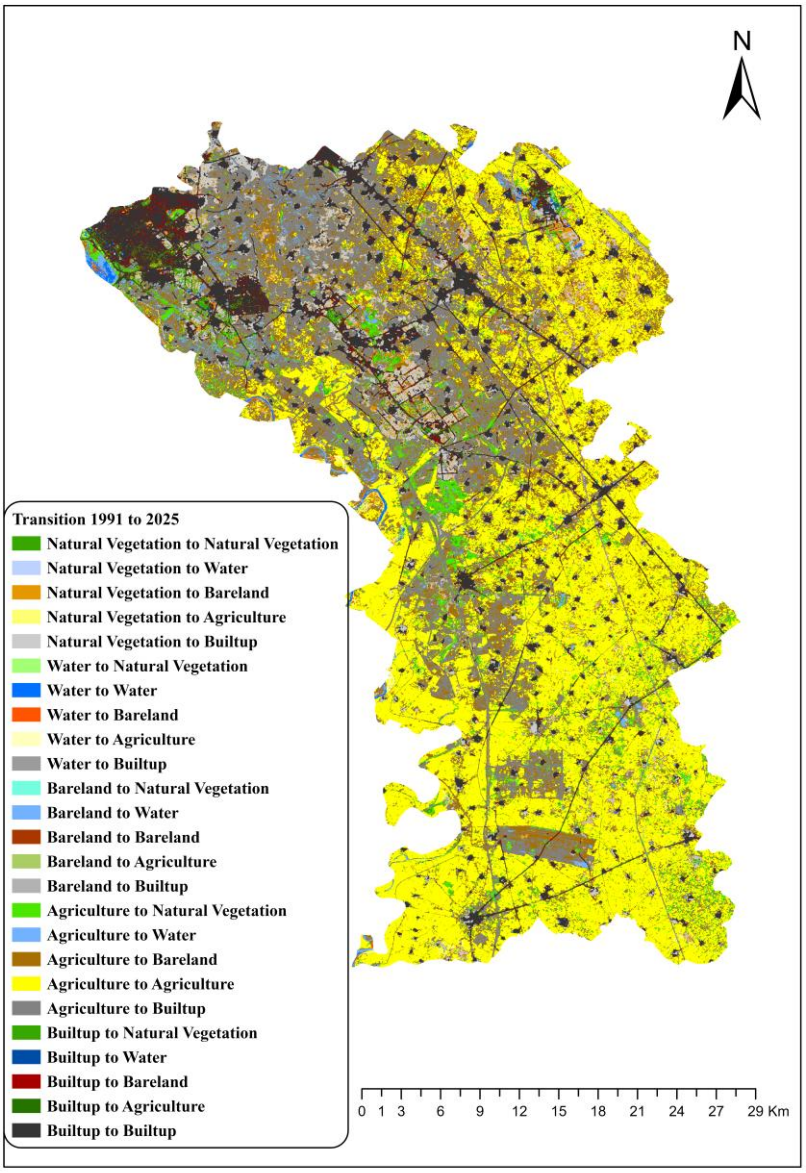


Figure 8: Cumulative Landscape Transformation Matrix for Gautam Buddha Nagar from 1991 to 2025.

Spatial transition patterns also indicate that the urban growth was highly concentrated along major transportation corridors, industrial clusters, expressway networks, and peri-urban interfaces, highlighting the corridor-oriented nature of landscape transformation in the Gautam Buddha Nagar district ; . The overall results of the transition matrix analysis suggest that the rapid urbanisation driven by infrastructure development has significantly altered the regional landscape layout and hastened ecological changes in the district during the last three decades.

4.4 Green–Grey Space Coordination Index (GGSCI)

The Green–Grey Space Coordination Index (GGSCI) analysis using the 500 m fishnet framework shows high geographical and temporal heterogeneity of the ecological–urban balance in Gautam Buddha Nagar district during 1991–2025. The fishnet-based framework provides a more refined description of local interactions between ecological green spaces and the growth of grey infrastructure compared to traditional buffer-based methods, thereby allowing a more detailed assessment of ecological imbalance and urban transformation processes in the district, as displayed in Figure 9(a–e).

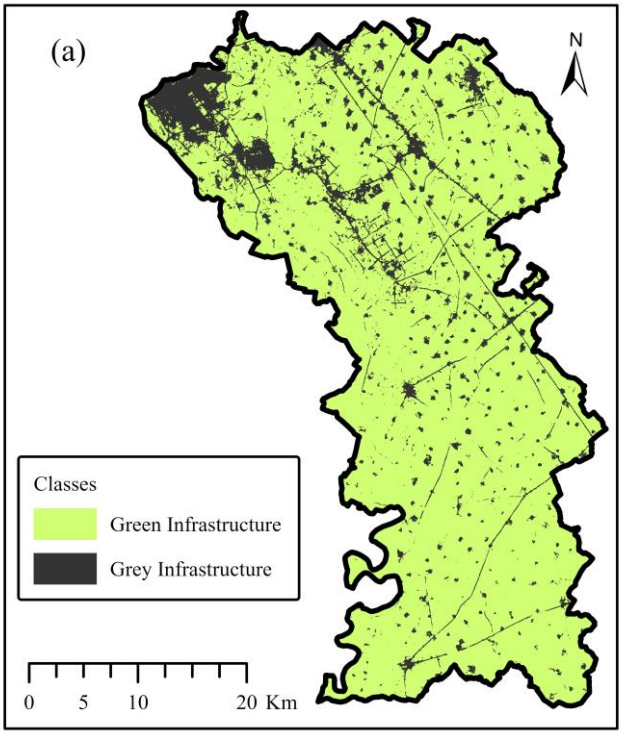


Figure 9 (a): Footprints of Green and Grey Infrastructure in 1991

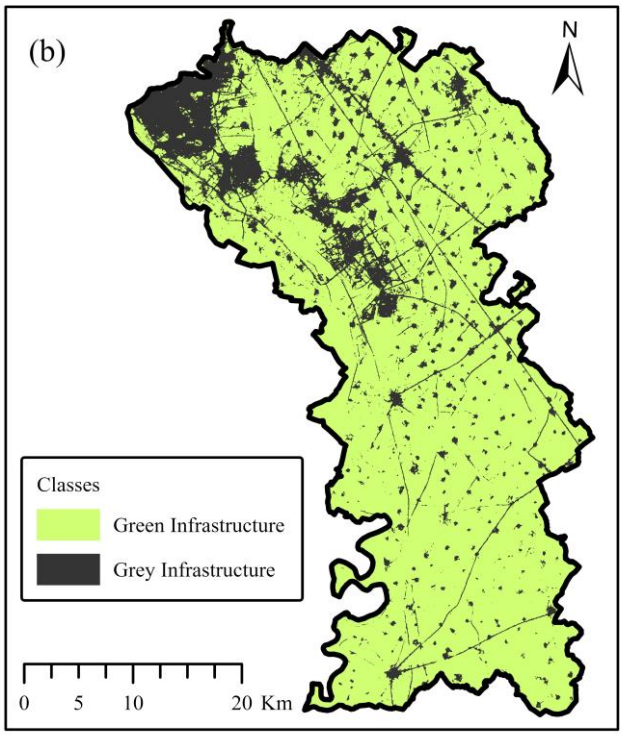


Figure 9 (b): Footprints of Green and Grey Infrastructure in 2001

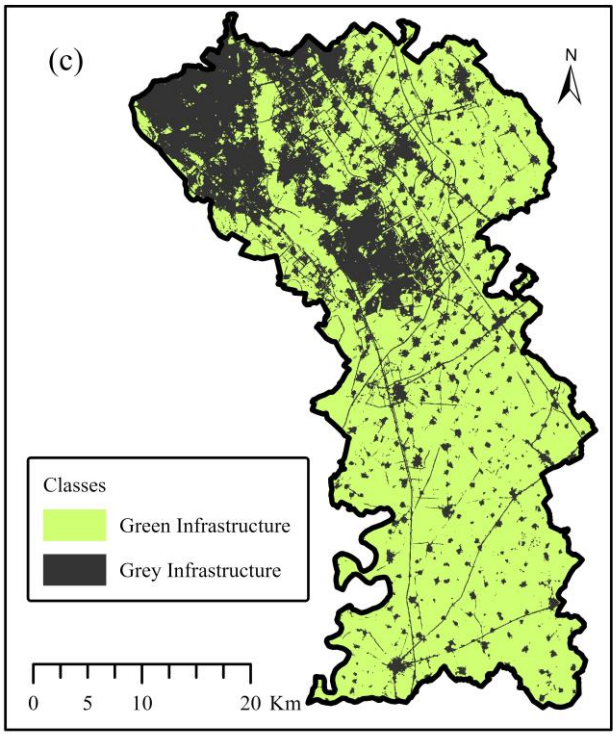


Figure 9 (c): Footprints of Green and Grey Infrastructure in 2011

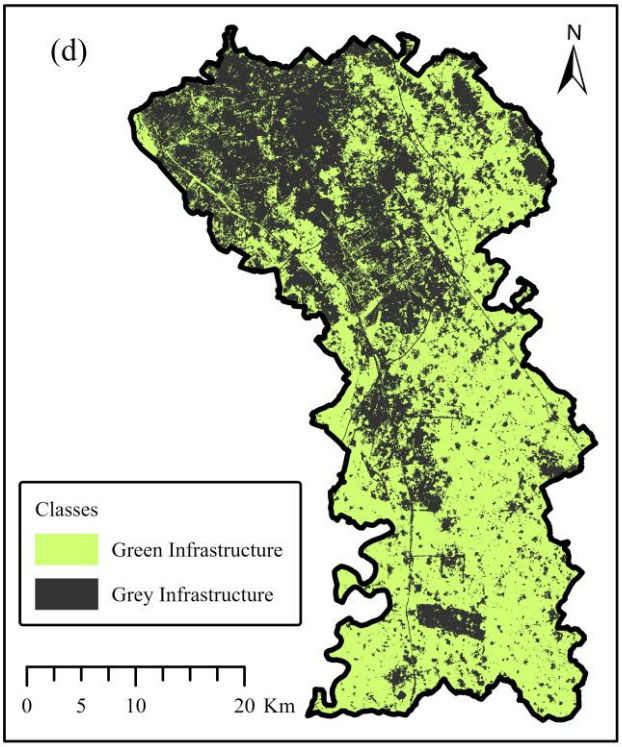


Figure 9 (d): Footprints of Green and Grey Infrastructure in 2021

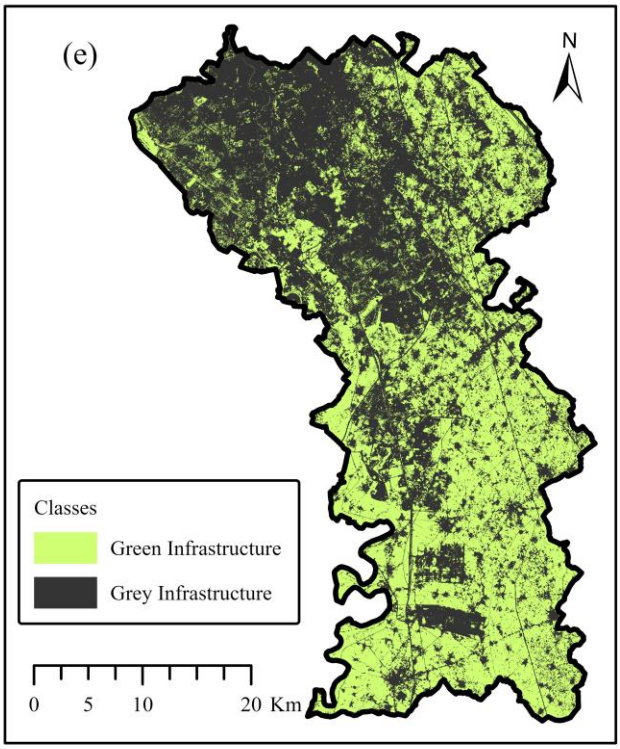


Figure 9 (e): Footprints of Green and Grey Infrastructure in 2025

Urban green spaces represent ecologically functioning landscapes with vegetation cover, hydrological management, ecological continuity, and environmental stability, while grey spaces are mostly anthropogenic surfaces associated with infrastructure development and urban expansion. The integration of green and grey spatial components offers a quantitative framework to assess the ecological-urban balance and to locate places undergoing rapid landscape modification ; . The spatial distribution of annual GGSCI values presented in Figure 10(a–e) indicates a gradual increase in mean coordination values throughout the study period, although the spatial distribution of ecological–urban balance remained highly uneven across the district. The mean GGSCI values increased from 0.156 in 1991 to 0.184 in 2001, 0.240 in 2011, 0.343 in 2021, and 0.413 in 2025. The increase is mainly due to the ongoing redistribution, fragmentation, and rearrangement of green and grey spaces inside the fast-urbanising terrain. However, despite the overall increase in mean coordination values, several urban cores and infrastructural corridors continued to display considerable ecological imbalance, typified by overwhelming grey-space expansion and deteriorating ecological continuity.

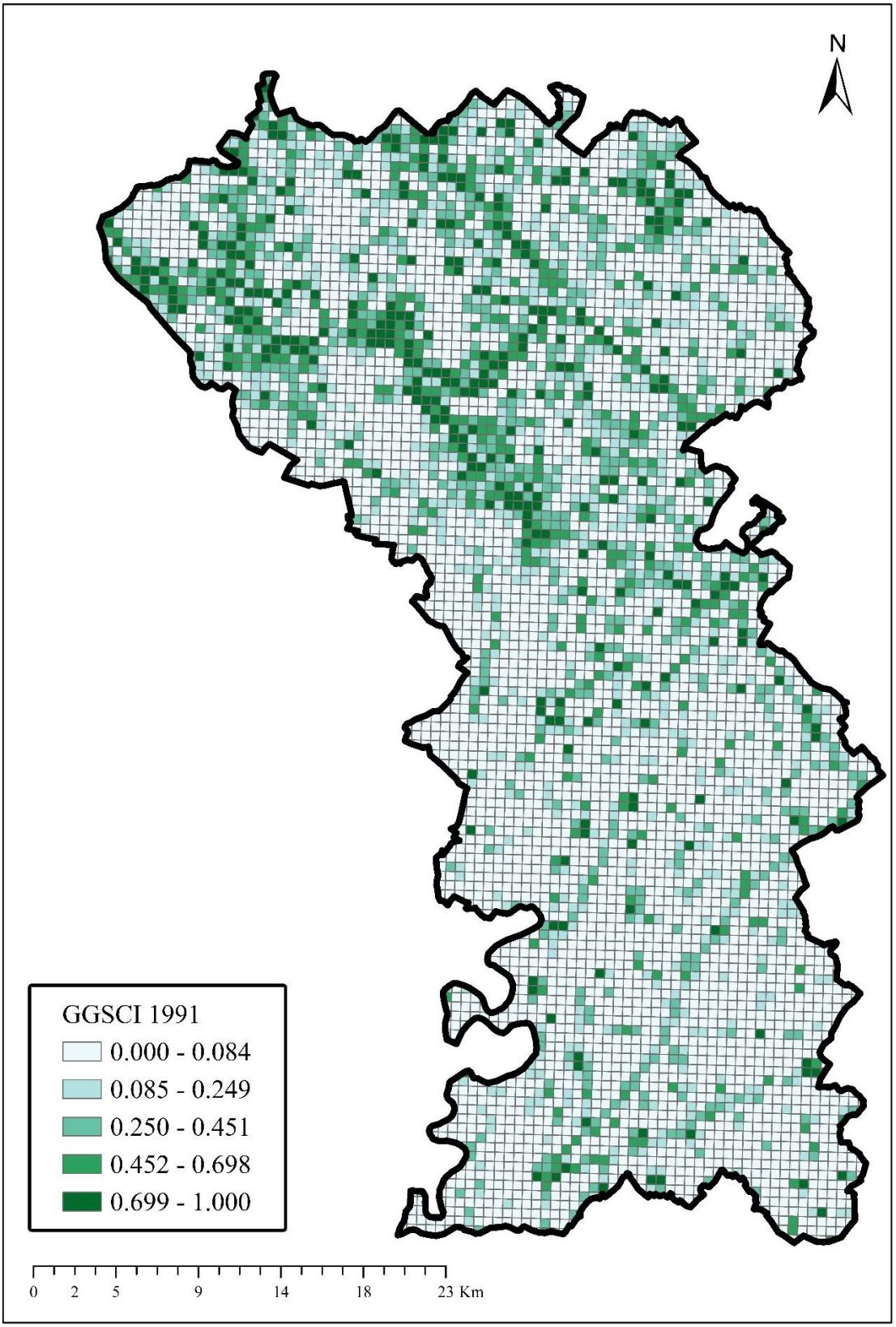


Figure 10 (a): Spatial Distribution of Annual Green-Grey Space Coordination Index (GGSCI) - 1991

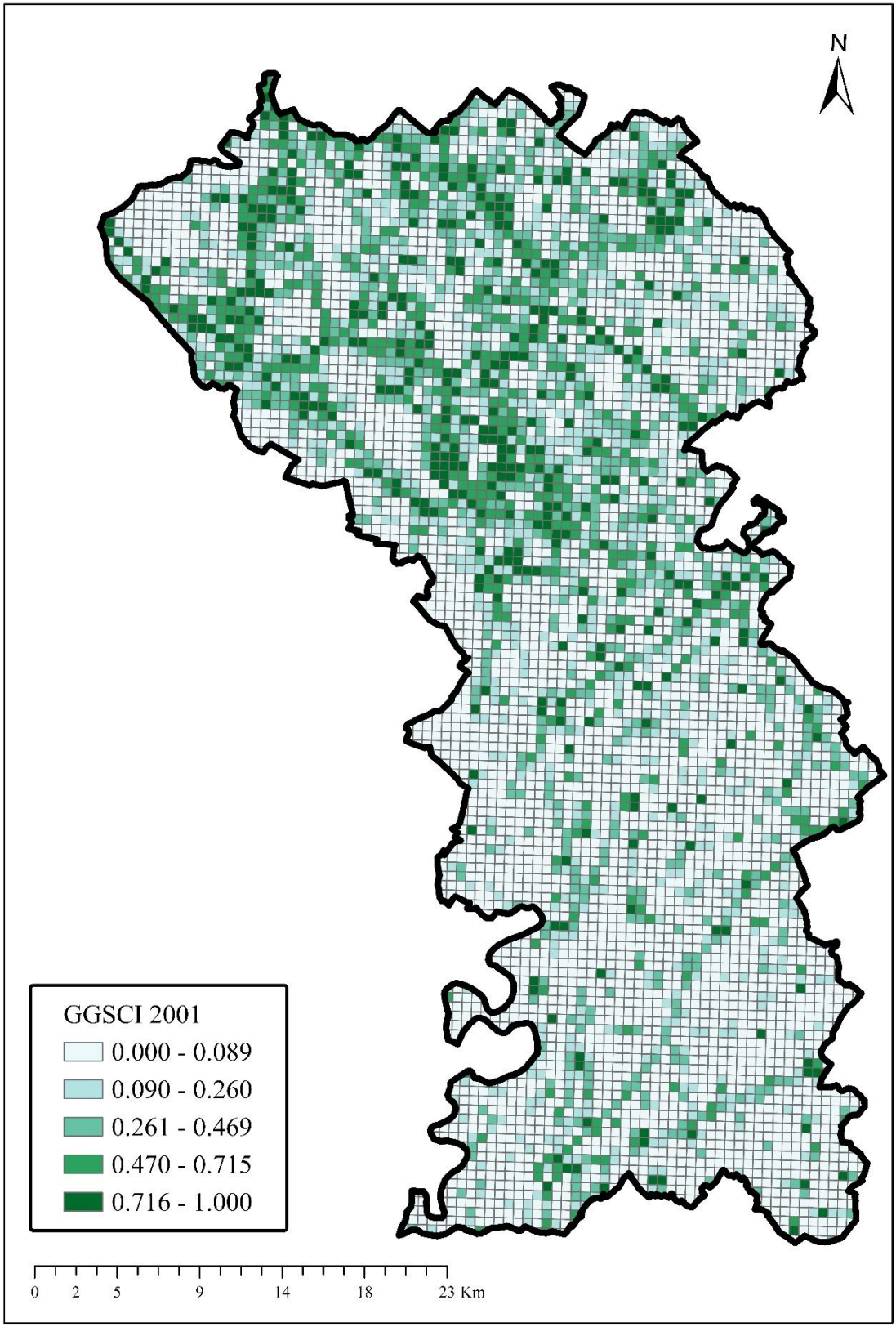


Figure 10 (b): Spatial Distribution of Annual Green-Grey Space Coordination Index (GGSCI)- 2001

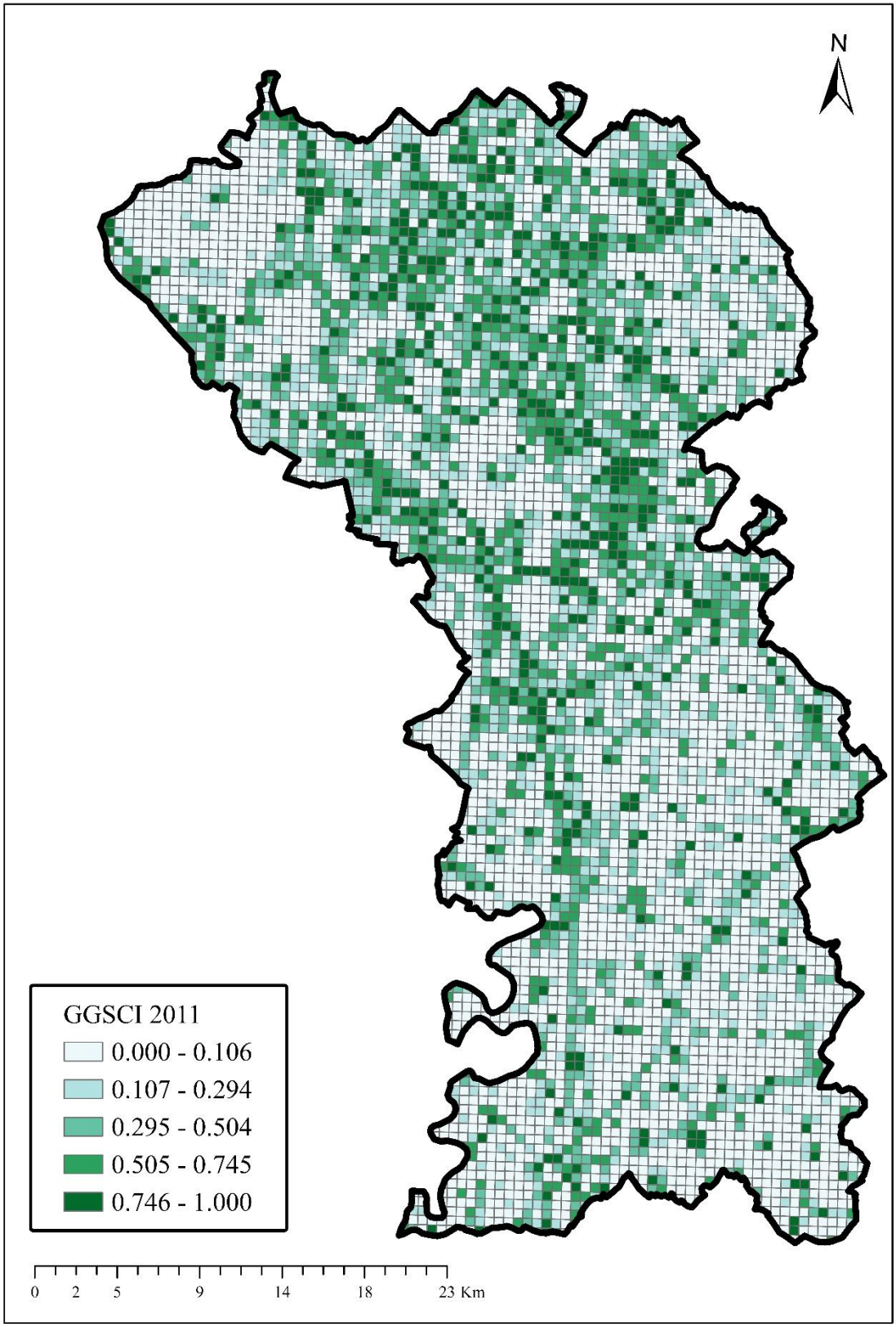


Figure 10 (c): Spatial Distribution of Annual Green-Grey Space Coordination Index (GGSCI)-2011

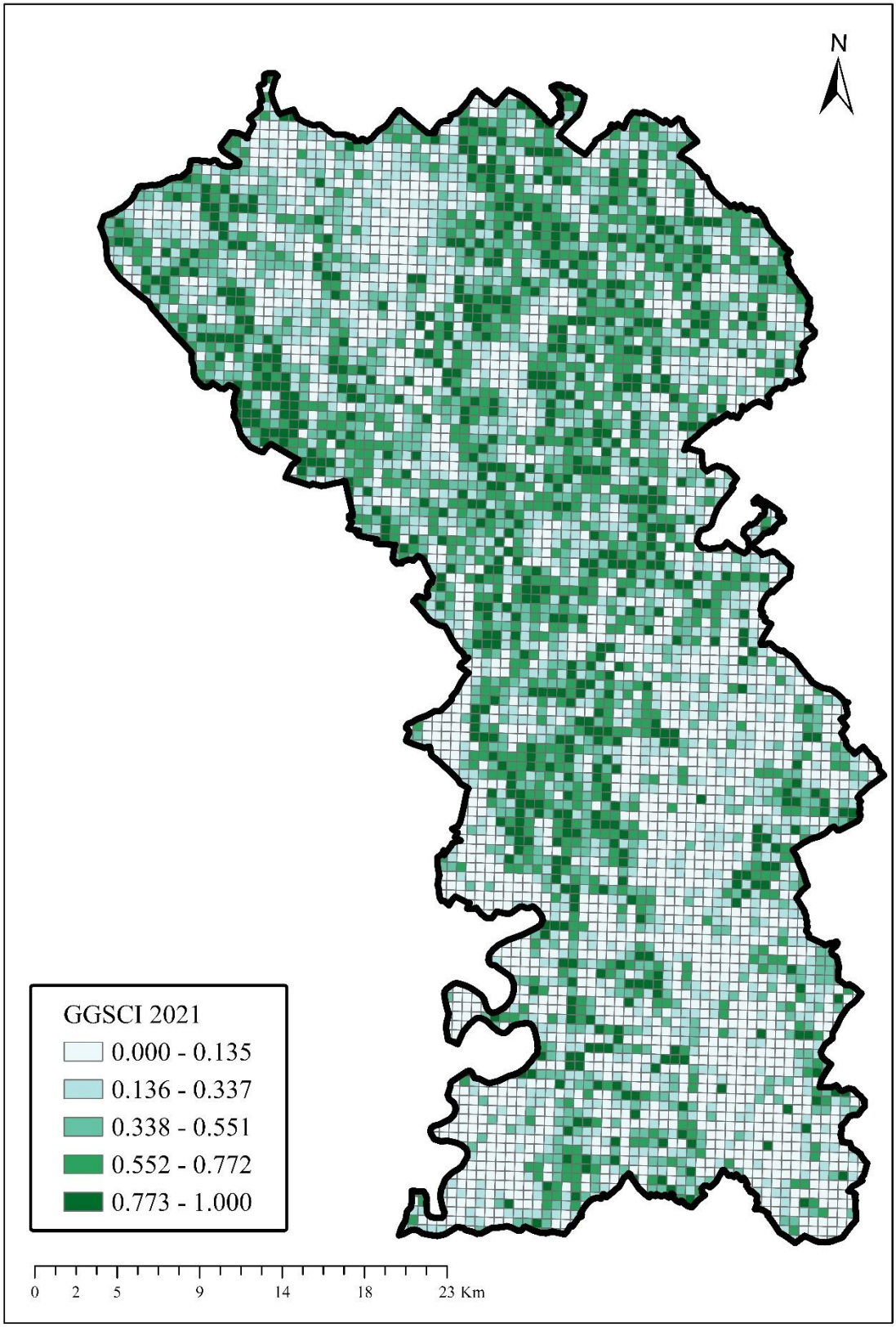


Figure 10 (d): Spatial Distribution of Annual Green-Grey Space Coordination Index (GGSCI)-2021

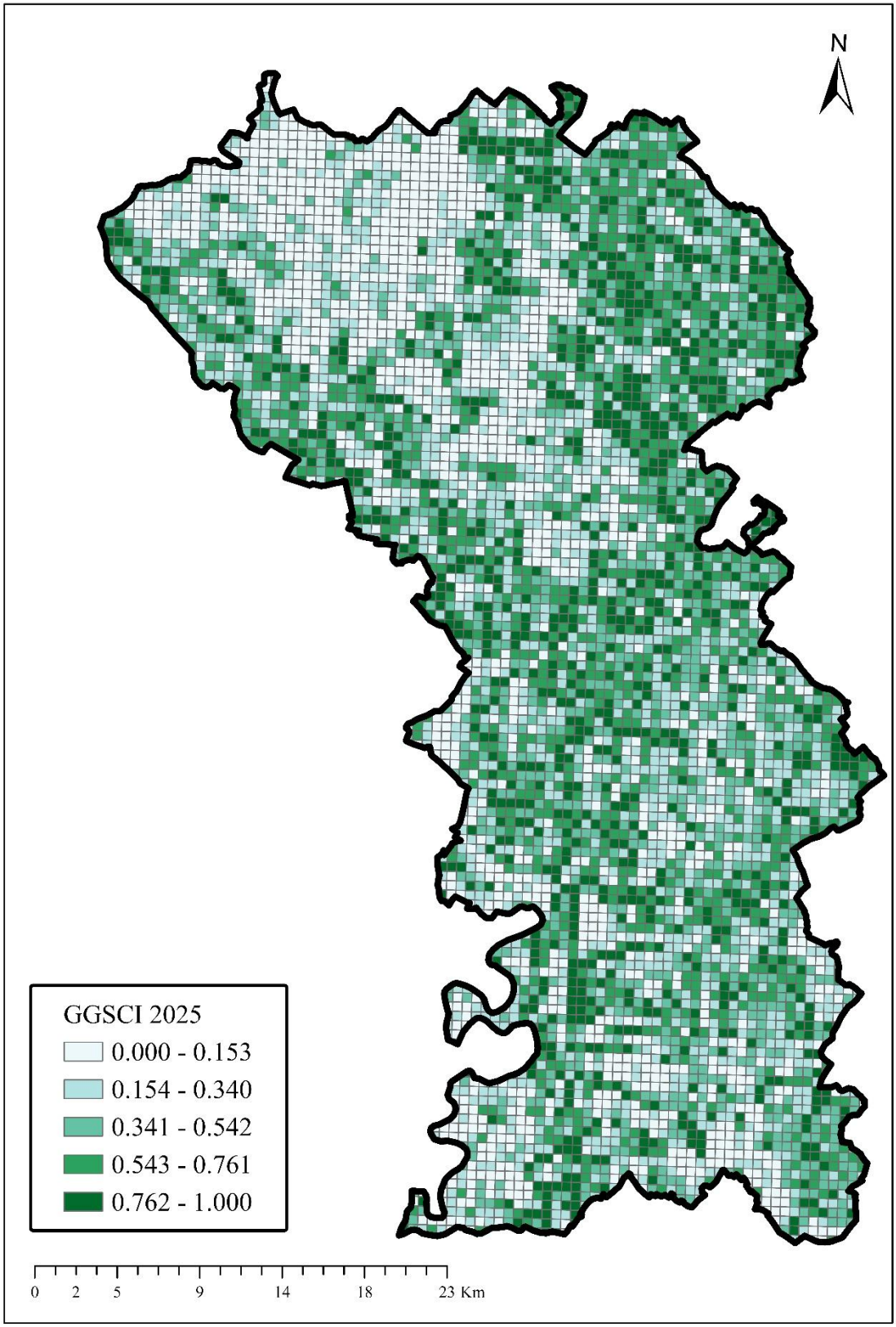


Figure 10 (e): Spatial Distribution of Annual Green-Grey Space Coordination Index (GGSCI)-2025

The spatial distribution of GGSCI further demonstrates that Noida, Greater Noida, and rapidly urbanising peri-urban sectors experienced strong grey-space concentration associated with large-scale built-up expansion, construction activity, and continuous land transformation processes, as clearly visible in Figure 10(a–e). In contrast, peripheral regions retained comparatively higher ecological continuity due to the persistence of agricultural landscapes, vegetated surfaces, and lower infrastructure intensity. These spatial patterns collectively indicate substantial heterogeneity in ecological–urban interactions across different parts of the district.

The spatial variation in absolute GGSCI change across different temporal intervals is illustrated in Figure 11(a–e). The temporal change in GGSCI further highlights the dynamic nature of ecological restructuring during distinct phases of urban expansion. The mean GGSCI change values were 0.028 during 1991–2001, 0.056 during 2001–2011, 0.104 during 2011–2021, and 0.069 during 2021–2025, while the overall mean change for the entire study period (1991–2025) was 0.256. The greatest positive change was observed during 2011–2021, indicating substantial reorganisation of green and grey spatial patterns during the phase of accelerated metropolitan growth and infrastructure expansion. Nevertheless, the spatial variability of GGSCI change remained highly heterogeneous, with several fishnet cells recording strong negative values associated with rapid grey infrastructure growth and ecological decline.

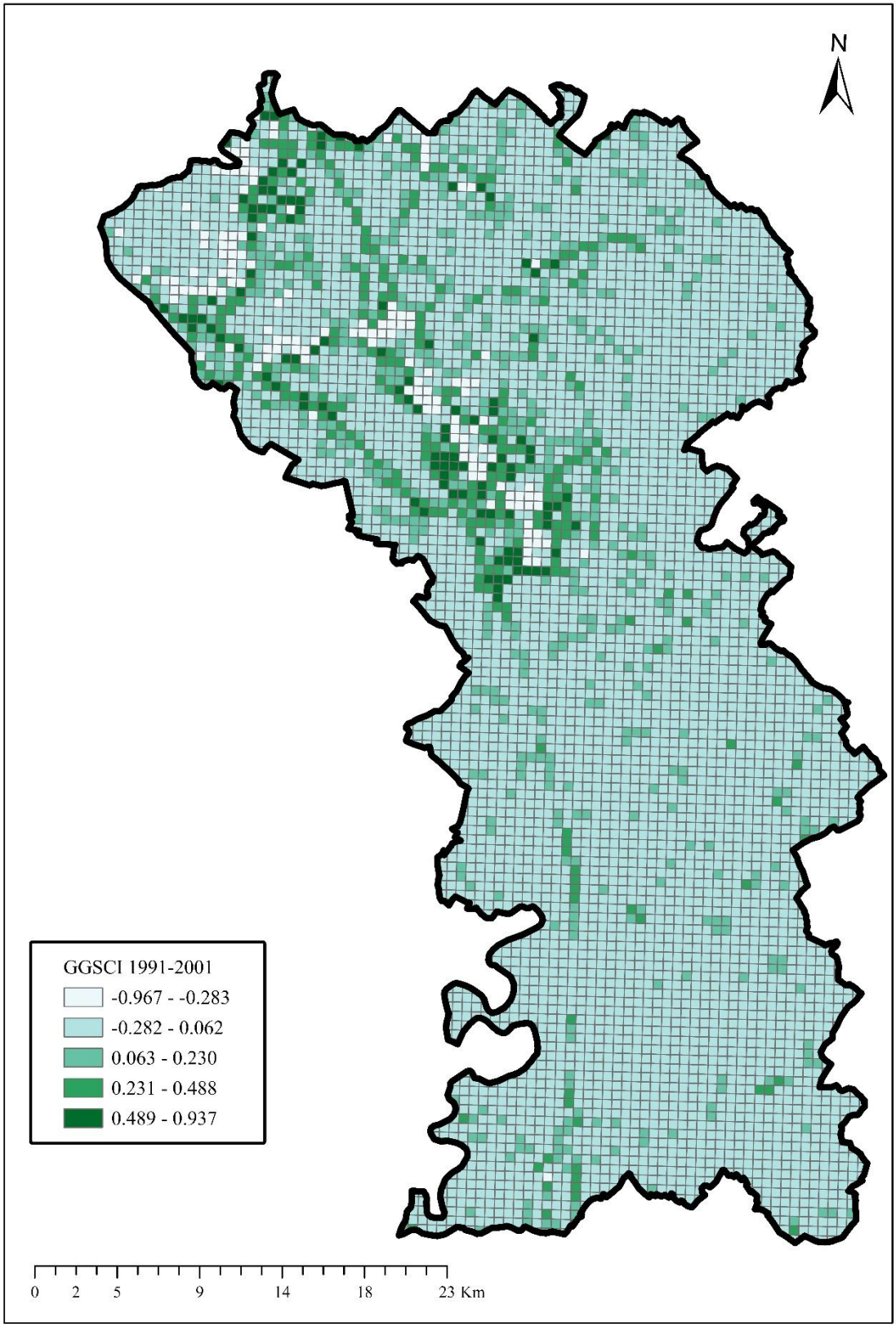


Figure 11 (a): Absolute Change in Green-Grey Space Coordination Index Across Epochs, 1991-2001

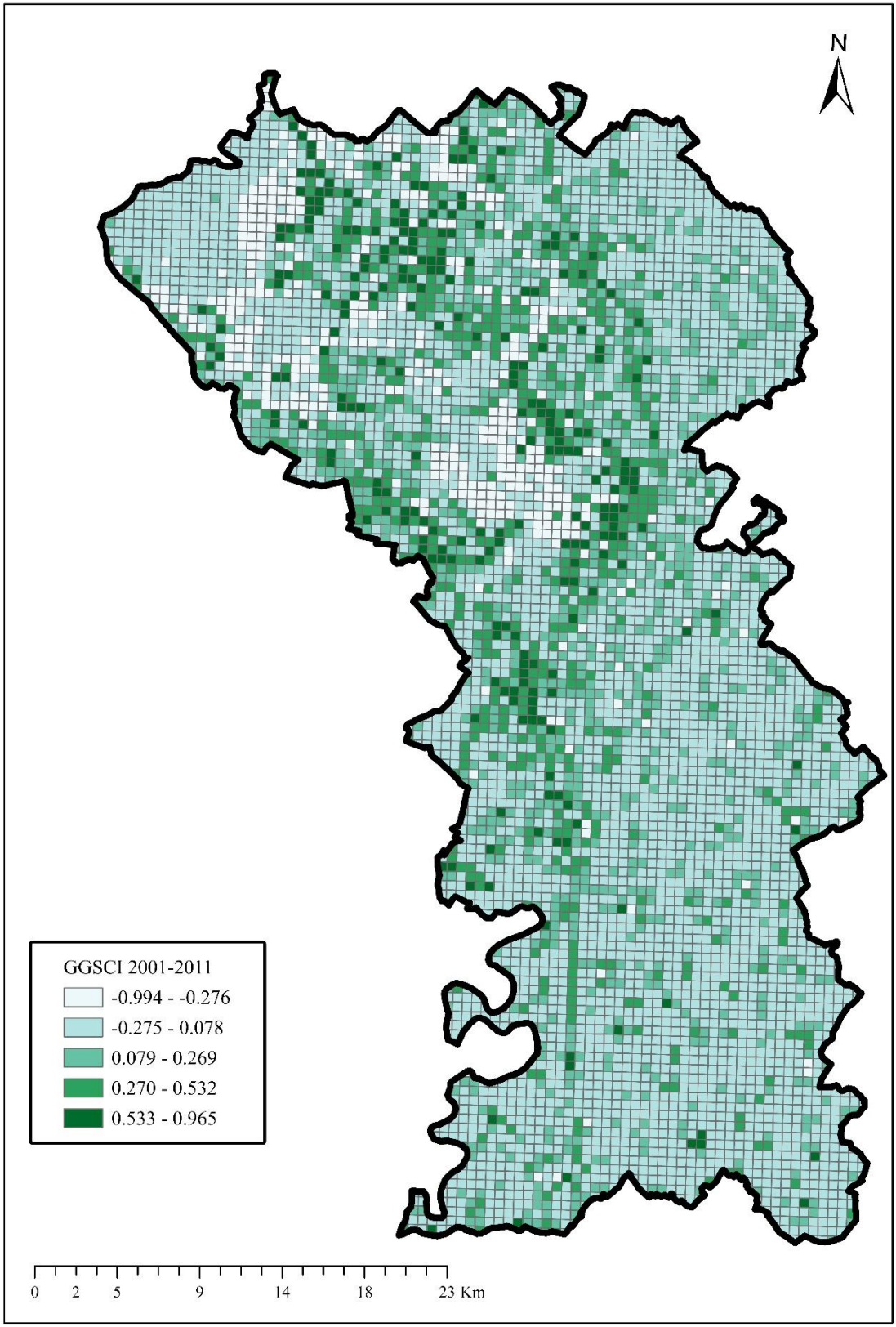


Figure 11 (b): Absolute Change in Green-Grey Space Coordination Index Across Epochs, 2001-2011

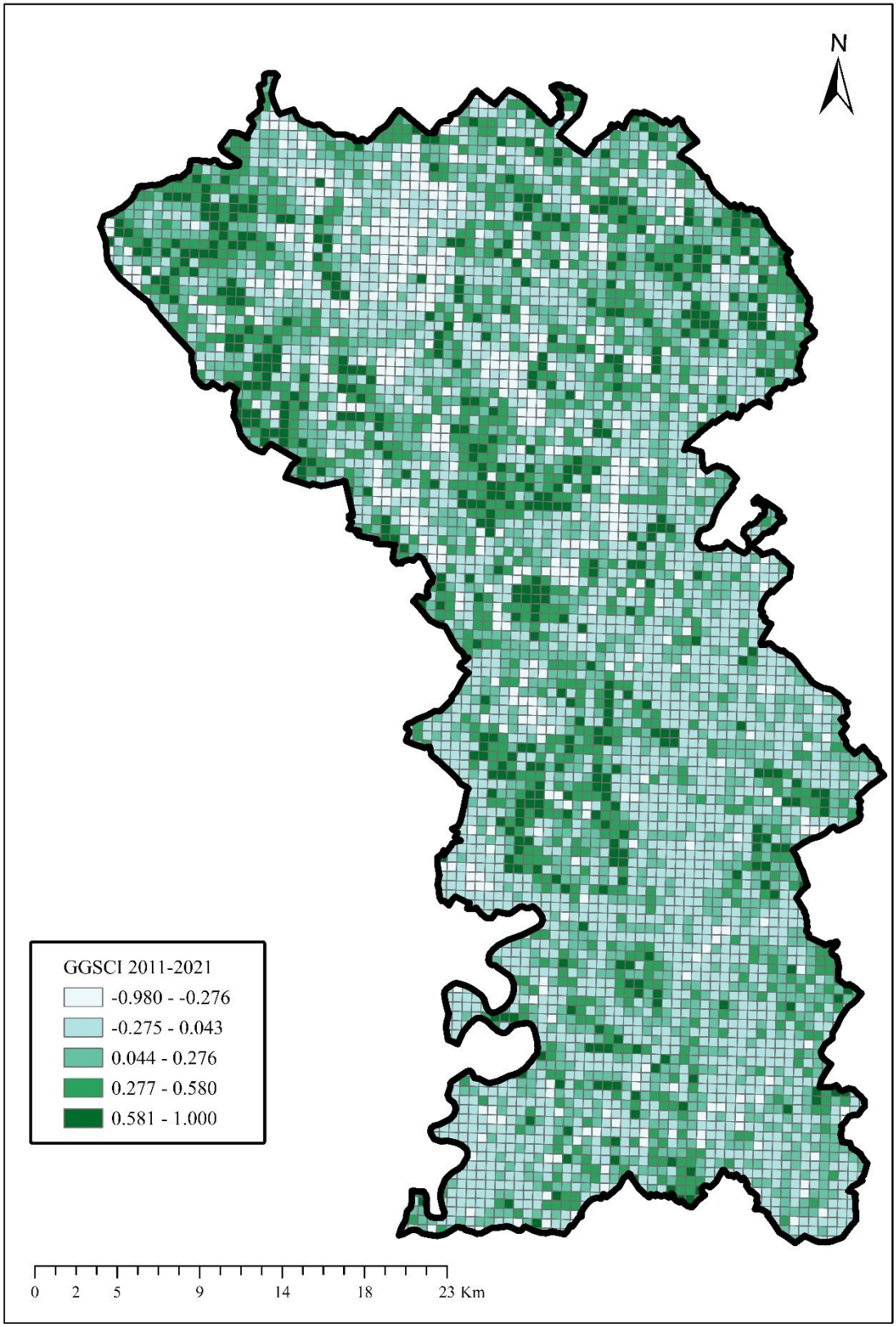


Figure 11 (c): Absolute Change in Green-Grey Space Coordination Index Across Epochs, 2011-2021

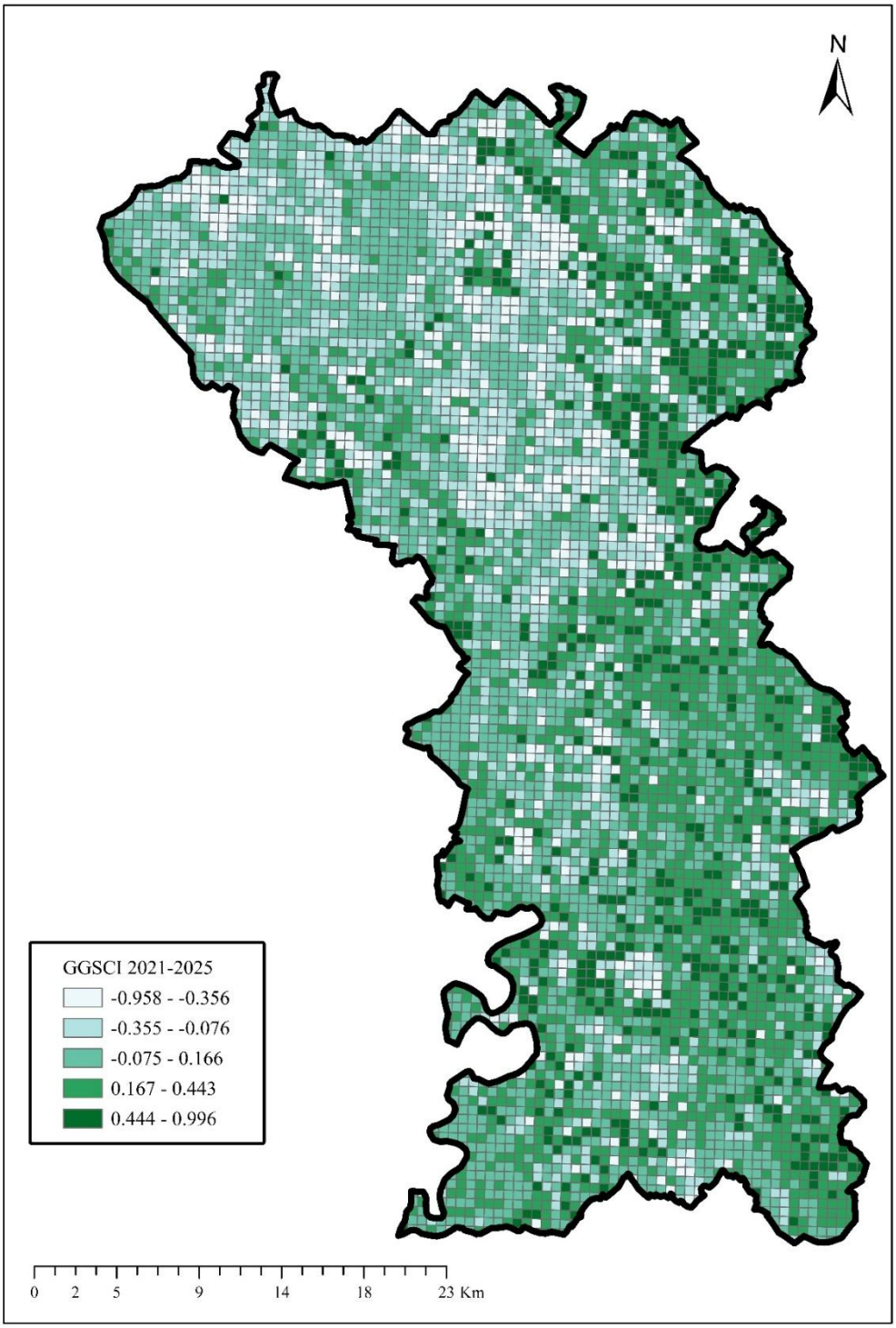


Figure 11 (d): Absolute Change in Green-Grey Space Coordination Index Across Epochs, 2021-2025

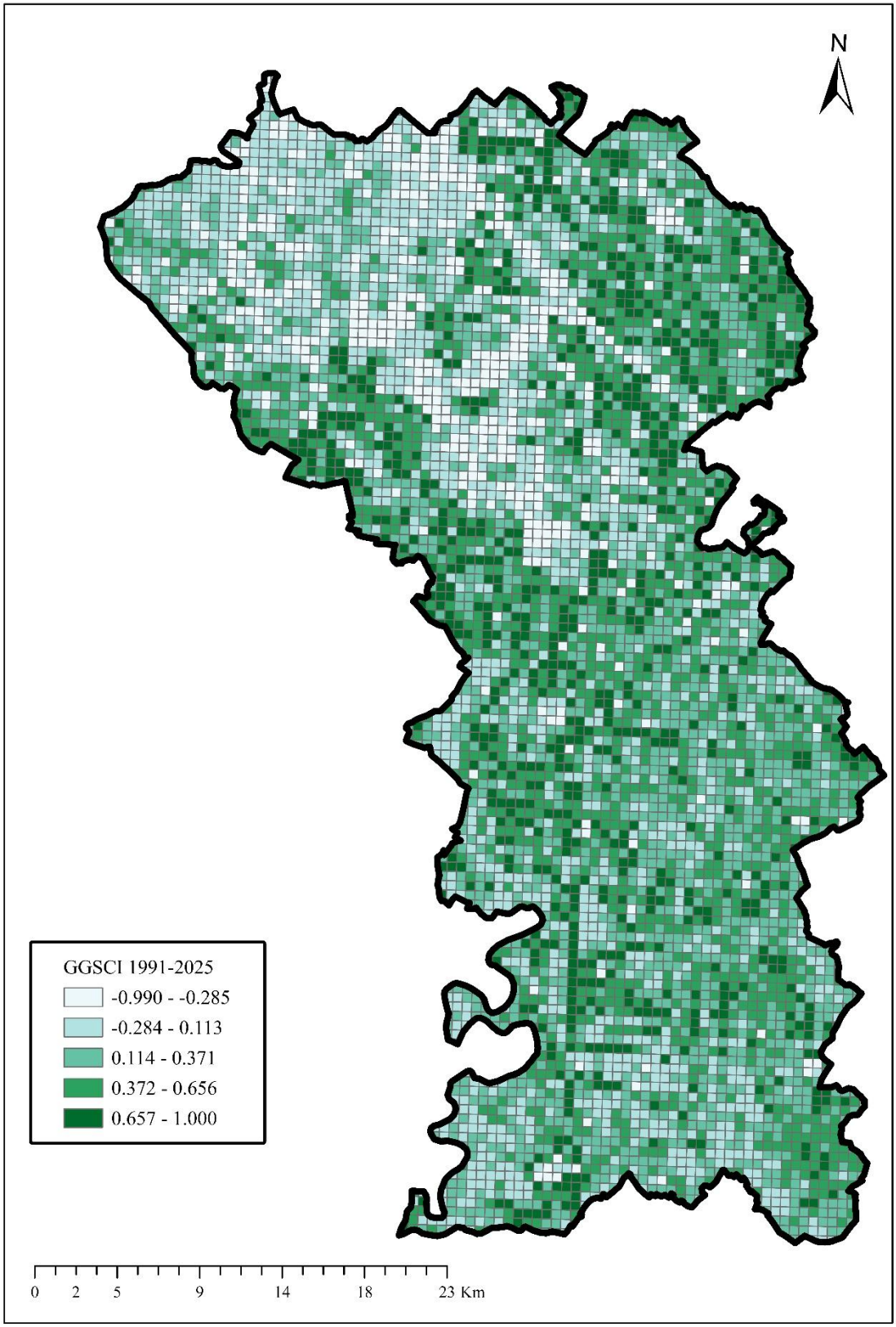


Figure 11 (e): Absolute Change in Green-Grey Space Coordination Index Across Epochs, 1991-2025

Negative GGSCI change values were predominantly concentrated around major expressway corridors, industrial zones, construction clusters, and newly urbanised regions, where built-up and bareland categories expanded at the expense of agricultural and vegetated landscapes. These areas represent zones of intensified anthropogenic disturbance and rapid peri-urban transformation. Conversely, positive GGSCI change values were more commonly observed in peripheral and relatively less urbanised sectors, where ecological landscapes remained comparatively stable and urban expansion intensity was lower.

The long-term annual rate of ecological–urban transformation across Gautam Buddha Nagar district is presented in Figure 12. The Annual GGSCI Rate further demonstrates the intensity of long-term ecological–urban transformation across the district. The mean annual GGSCI rate for 1991–2025 was approximately 0.0075, although individual fishnet cells ranged from −0.029 to 0.029, indicating substantial localised variation in ecological balance and urban transformation intensity. Positive annual GGSCI rates were generally associated with relatively stable ecological landscapes and lower levels of infrastructure expansion, whereas strongly negative annual rates were concentrated in highly urbanised sectors characterised by continuous land conversion and grey-space dominance, as reflected in Figure 12.

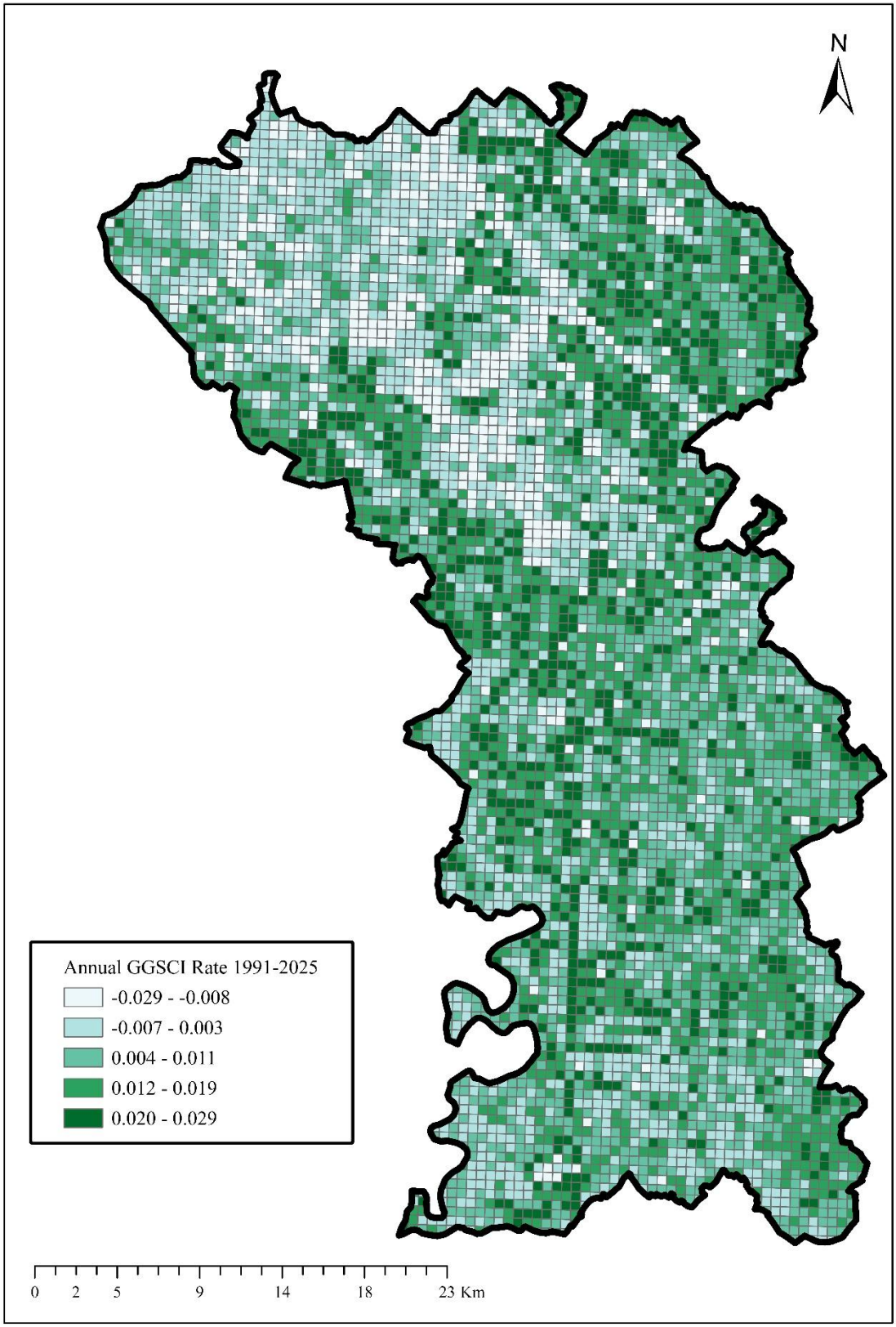


Figure 12: Change in the Annual Rate of the Green-Grey Space Coordination Index (1991 – 2025)

Overall, the GGSCI analysis demonstrates that Gautam Buddha Nagar district has undergone substantial ecological restructuring during the past three decades. The fishnet-based framework effectively captures micro-level spatial heterogeneity and highlights the coexistence of relatively preserved ecological landscapes and rapidly intensifying grey infrastructure zones. The results further indicate that infrastructure-led urbanisation has progressively altered the green–grey spatial balance of the district, particularly after 2011, intensifying ecological pressure, landscape fragmentation, and environmental transformation within the rapidly expanding metropolitan environment.

5 Discussion

5.1 Agricultural Land Conversion as the Principal Driver of Urban Expansion

The results show that the main process of urban sprawl in Gautam Buddha Nagar district during 1991–2025 is the conversion of agricultural land. The analysis of the transition matrix reveals that the change from agriculture to built-up land was the primary land transformation pathway for all time intervals, growing from about 92.5 km² in 1991–2001 to over 164.7 km² in 2021–2025 (Figure 3-8). The rapid spatial expansion of Noida, Greater Noida, industrial corridors, transportation infrastructure, and peri-urban residential development in connection with the greater metropolitan boom of the National Capital Region (NCR) is driving this trend. The findings emphasise the importance of agricultural landscapes as the main land reserve for the infrastructure-led urbanisation occurring in fast-rising metropolitan regions (Hashem Dadashpoor, 2019; Liqun Sun, 2020). Urban growth within the district exhibited a strong corridor-oriented spatial pattern, primarily concentrated along expressways, transportation networks, and industrial development zones, clearly visible in Figure 2(a–e). Similar spatial restructuring patterns have been observed in rapidly urbanising peri-urban regions where transportation infrastructure acts as a major catalyst for landscape transformation and urban sprawl. Natural vegetation exhibited a continuous decline throughout the study period, indicating increasing ecological fragmentation and reduction of ecologically functional landscapes. At the same time, bareland rose significantly after 2011 because of construction operations, land excavation, unoccupied plots, and transitional development surfaces connected with continued urban expansion . The simultaneous development in the built-up and bareland classes reflects the very dynamic and transitional nature of peri-urban environments in the Gautam Buddha Nagar district. These patterns also suggest that the urbanisation inside

the district is still an active, ongoing process, with rapid spatial rearrangement and land modification, as seen in Figures 2(a–e) and 7.

5.2 Spatial Dynamics of Green and Grey Spaces

The Green–Grey Space Coordination Index (GGSCI) analysis based on the 500 m fishnet framework reveals substantial spatial heterogeneity in ecological–urban balance across Gautam Buddha Nagar district, as illustrated in Figure 9(a–e) and Figure 10(a–e). The fishnet-based approach effectively captures localised variability in the distribution of ecological green spaces and urban grey infrastructure within heterogeneous urban and peri-urban environments. Compared with generalised concentric buffer approaches, the fishnet framework provides a finer spatial representation of ecological imbalance and localised urban transformation processes. The results indicate that urban cores such as Noida and Greater Noida are predominantly characterised by grey-space dominance associated with extensive built-up surfaces, transportation infrastructure, industrial clusters, and construction-related bareland, as clearly visible in Figure 10(a–e). Peripheral agricultural regions, on the other hand, have significantly higher concentrations of green space and reasonably balanced ecological circumstances. Similar geographical patterns have been observed in fast-urbanising metropolitan areas with decreasing ecological coordination within dense urban centres, while transitional peri-urban landscapes maintain better ecological continuity . The average GGSCI values showed a progressive increase from 1991 to 2025; the observed increase is mainly attributed to the redistribution and spatial reconfiguration of green and grey spaces, not a uniform improvement of ecological conditions. The results indicate that in several urban sectors, ecological balance is maintained mainly through institutional green spaces, regulated open areas, compensatory plantation activities, and fragmented vegetated patches and not through integrated ecological planning and landscape-level environmental management.

5.3 Temporal Variability in Ecological–Urban Coordination

The temporal evolution of GGSCI demonstrates that ecological–urban interactions within Gautam Buddha Nagar district became increasingly dynamic during the later stages of urbanisation, as illustrated in Figure 11(a–e). The highest GGSCI change was observed during 2011–2021, corresponding with the rapid expansion of transportation infrastructure, industrial zones, institutional development, and peri-urban residential growth. This period represents a major phase of landscape restructuring and redistribution of green and grey spatial components

across the district. Despite the overall increase in mean GGSCI values, strong local variability persisted throughout the study period. Several fishnet cells recorded negative GGSCI change values, particularly near expressways, industrial corridors, and newly urbanised regions where grey-space expansion exceeded ecological growth. These spatial patterns indicate increasing ecological imbalance within rapidly developing urban sectors. Negative GGSCI change values were predominantly associated with intensified built-up expansion, construction activities, and declining agricultural and vegetated landscapes. The Annual GGSCI Rate further highlights the uneven nature of ecological transformation across the district, as presented in Figure 12. Positive annual rates were primarily concentrated within peripheral agricultural regions where ecological landscapes remained comparatively stable, whereas urban cores and rapidly transforming peri-urban zones exhibited negative rates associated with the continuous expansion of impervious surfaces. Similar trends have been documented in other rapidly urbanising metropolitan environments where ecological coordination remains spatially heterogeneous during phases of accelerated urban growth (Wan-Ben Wu, 2021; Zeng, 2022).

5.4 Urban Expansion and Emerging Ecological Pressure

The integrated result of LULC categorisation, transition matrix analysis, alluvial visualisation, and GGSCI assessment shows that Gautam Buddha Nagar district is experiencing rapid and spatially uneven urban transformation, as shown in Figure 2(a–e), Figure 7 and Figure 8. The expansion of built-up areas has mainly taken place at the expense of the agricultural and natural landscape, therefore aggravating the environmental pressure throughout the whole metropolitan region. As the number of impervious surfaces increases progressively, many ecological challenges arise, such as increasing land surface temperature, decreasing groundwater recharge, habitat fragmentation, increasing runoff generation and reduced environmental resilience (Karen C. Seto B. G., 2012; Heather A. Sander, 2015). The substantial increase in bareland during recent years further reflects the transitional nature of peri-urban development processes. These exposed surfaces primarily represent construction zones, land excavation areas, vacant plots, and fragmented urban edges associated with ongoing infrastructure expansion. Such landscapes intensify thermal stress, ecological disturbance, and hydrological instability within rapidly urbanising environments. The alluvial diagrams further demonstrate that agricultural land continuously supplied the largest proportion of land for urban expansion, while vegetation fragmentation and transitional barren surfaces simultaneously increased, as illustrated in Figure 3–7. These patterns highlight the complex

and dynamic characteristics of peri-urban transformation in Gautam Buddha Nagar district and demonstrate the increasing ecological pressure associated with infrastructure-led metropolitan growth.

5.5 Planning Implications and Sustainable Urban Development

The findings of this study have significant implications for sustainable urban design and ecological management of fast-growing metropolitan areas. The fishnet-based GGSCI framework was capable of detecting localised ecological imbalance and spatial variability in green–grey distribution as depicted in Figure 10(a–e), Figure 11(a–e) and Figure 12. Compared with conventional buffer-based approaches, the fishnet framework provides a finer spatial representation of ecological stress zones and localised environmental transformation within heterogeneous peri-urban landscapes. The results suggest that planning strategies within Gautam Buddha Nagar district should vary according to local levels of urbanisation intensity and ecological pressure. Urban cores require stronger protection of remaining green spaces, ecological corridors, urban water bodies, and environmentally sensitive landscapes to improve ecological resilience and environmental quality. In contrast, rapidly transforming peri-urban regions should prioritise the conservation of agricultural buffers, connected green infrastructure, and ecological transition zones before irreversible land transformation occurs. The study also contributes to Sustainable Development Goal (SDG) 11, which emphasises sustainable cities and communities, and SDG 15, which focuses on terrestrial ecosystem conservation and ecological sustainability within urbanising environments. Furthermore, the integration of transition matrix analysis, alluvial visualisation, and fishnet-based GGSCI assessment provides a comprehensive framework for evidence-based ecological planning, long-term urban monitoring, and sustainable metropolitan development.

5.6 Limitations of the Study

Certain limitations of the study should be acknowledged. The analysis was conducted using five temporal datasets, which may not fully capture short-term fluctuations and seasonal variations associated with land transformation processes. Although Landsat imagery provides consistent and reliable long-term coverage for regional urban growth analysis, the 30 m spatial resolution may not adequately detect very small or highly fragmented land-cover changes occurring within dense peri-urban environments. Additionally, the interpretation of historical land-cover conditions for earlier years partly relied on ancillary datasets and visual

interpretation techniques, which may introduce minor uncertainties within the classification process. The green–grey binary framework also simplifies complex ecological processes into broader functional categories and should therefore be interpreted as an indicator of spatial ecological coordination rather than a complete representation of ecological health and environmental quality. Future studies may incorporate higher-resolution satellite imagery, more frequent temporal observations, advanced machine learning approaches, and additional ecological indicators to further improve the understanding of urban ecological transformation within Gautam Buddha Nagar district and other rapidly urbanising metropolitan regions.

6 Conclusion

This study investigates the spatio-temporal dynamics of Land Use/Land Cover (LULC), land transformation processes, and Green–Grey Space Coordination Index (GGSCI) in Gautam Buddha Nagar district from 1991 to 2025 using Remote Sensing and GIS techniques. By integrating LULC classification, transition matrix analysis, alluvial visualisation, and a fishnet-based GGSCI framework, the study provides a comprehensive understanding of urban ecological transformation within one of the fastest-growing metropolitan regions of the National Capital Region (NCR).

The results indicate that the increasing urbanisation driven by infrastructure has dramatically transformed the regional landscape structure during the past three decades. The built-up area and transitional bareland surfaces exhibited continuous increase, whereas agricultural land and natural vegetation showed significant decline over the research period. Transition matrix analysis demonstrated that agriculture-to-built-up conversion remained the dominant land transformation pathway across all temporal intervals, highlighting the strong influence of corridor-oriented urban growth associated with transportation infrastructure, industrial development, and peri-urban residential expansion. The alluvial visualisation further confirmed the continuity and magnitude of these transformation trajectories and emphasised the dynamic nature of peri-urban landscape restructuring within the district. These rapid land transformation processes further influenced the spatial relationship between ecological green spaces and urban grey spaces across the district. The fishnet-based GGSCI analysis revealed considerable spatial heterogeneity in ecological–urban balance across the Gautam Buddha Nagar district. Dominant grey-space concentration was related to intensive built-up growth and infrastructural expansion in urban cores such as Noida and Greater Noida, whereas peripheral regions maintained substantially higher ecological continuity and green-space concentration.

Although mean GGSCI values gradually increased during the study period, the results primarily reflect spatial redistribution and restructuring of green and grey spaces rather than uniform ecological improvement. Several rapidly urbanising sectors continued to exhibit localised ecological imbalance where grey-space expansion exceeded ecological growth.

In addition to revealing spatial ecological imbalance, the study further demonstrates that the fishnet-based GGSCI framework provides a more detailed representation of localised ecological–urban interactions compared with generalised buffer-based approaches. The framework is capable of capturing the micro-level spatial heterogeneity, ecological stress zones, and transitional urbanisation patterns in fast-changing peri-urban settings.

Overall, the results highlight that rapid infrastructure-driven urbanisation has substantially altered the ecological–urban balance within Gautam Buddha Nagar district and intensified localised ecological pressure in several rapidly developing peri-urban sectors. The increasing dominance of grey spaces and the continuous reduction of agricultural and vegetated landscapes may negatively affect long-term ecological resilience, environmental sustainability, and urban ecosystem stability if unmanaged urban expansion continues in the future.

Therefore, sustainable urban planning strategies incorporating ecological protection and environmentally sensitive land-use management are urgently required within the district. The protection of agricultural land, maintenance of urban green networks, restoration of ecological corridors, and implementation of ecologically sensitive planning regulations will be essential for improving long-term environmental sustainability and ecological continuity within rapidly urbanising landscapes.

The integrated geospatial framework developed in this study provides an effective approach for evaluating urban ecological transformation and localised green–grey spatial interactions. The framework can also be applied to other rapidly urbanising metropolitan regions to support evidence-based urban planning, ecological monitoring, and sustainable urban growth management.

Funding

The research work is part of PhD funded by the University Grants Commission, Ministry of Human Resource Development, Govt. of India, through a PhD research fellowship.

Competing Interests

The authors have no conflicts of interest to declare

Data availability

All data generated and analysed during this study are made available on reasonable request to the corresponding author.

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable

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