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Spatio-Temporal Assessment of Urban Carbon Storage and Its Dynamics Using InVEST Model

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Abstract: Carbon storage estimates are essential for sustainable urban planning and development. This study examines the spatio-temporal effects of land use and land cover changes on the provision and monetary value of above- and below-ground carbon sequestration and storage during 2011, 2019, and the simulated year 2027 in Noida. The Google Earth Engine-Random Forests (GEE-RF) classifier, the Cellular Automata Artificial Neural Network (CA-ANN) model, and the InVEST-CCS model are some of the software tools applied for the analysis. The findings demonstrate that the above- and below-ground carbon storage for Noida is 23.95 t/ha. Carbon storage in the city increased between 2011 and 2019 by approximately 67%. For the predicted year 2027, a loss in carbon storage is recorded. The simulated land cover for the year 2027 indicates that if the current pattern continues for the next decade, the majority of the land will be transformed into either built-up or barren land. This predicted decline in agriculture and vegetation would further lead to a slump in the potential for terrestrial carbon sequestration. Urban carbon storage estimates provide past records to serve as a baseline and a precursor to study future changes, and therefore more such city-scale analyses are required for overall urban sustainability.

Keywords: Carbon Storage And Sequestration (CSS); Cellular Automata-Artificial Neural Network (CA-ANN) model; Google Earth Engine (GEE); Noida

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1. Introduction

Urban sustainability is directly connected to the Sustainable Development Goals (SDGs), such as the goals concerning Sustainable Cities and Communities (Goal 11), Responsible Consumption and Production (Goal 12), and Climate Action (Goal 14) [1]. The SDGs call for nationally owned and region-specific development plans or strategies [2]. Urban centres emanate three-fourths of the world's total carbon dioxide (CO_2) emissions resulting from several anthropogenic activities [3]; therefore, it is imperative that cities take the lead rather than just depending on national plans and strategies [4]. They can achieve sustainability by reducing their CO_2 emissions and aiming for carbon (C) neutrality through carbon storage and sequestration (CSS) [5].

According to the IPCC [6], the major five carbon pools of a terrestrial ecosystem involving biomass are above-ground biomass (AGB), below-ground biomass (BGB), dead wood, litter, and soil organic matter (SOC). AGB includes all the visible and living biomass above the soil-stem, branches, bark, seeds, and foliage and constitutes the major portion of the terrestrial carbon pool. Changes in the land use system have a direct impact on above-ground biomass. BGB includes all living roots excluding fine roots and plays a pivotal role by transferring and storing carbon in the soil. SOC is the carbon produced from decomposing plants, bacterial and fungal growth, and metabolic activities of living organisms, and is one of the major contributors to carbon stocks [7]. Given that they only make up a small portion of the carbon stocks in forests, the dead mass of litter and woody debris is not a significant carbon sink [8]. The aggregate amount of C stored in the terrestrial C pools at any specified time is the carbon stock or store. The change in carbon stocks over time due to natural or anthropogenic activities gives the amount of C sequestered in the C pools. One of the essential prerequisites for cities to achieve C neutrality and sustainability is to have an accurate evaluation of the C sequestration potential of the urban greens [9]. The ability of urban greens to lock in C and mitigate elevated CO_2 levels has caught the attention of the research community all over the world [10–13].

Understanding land use dynamics and their effect on C sequestration capacity is vital for sustainable urban development. Land processes have a pivotal role in the global and regional C cycle through photosynthesis, respiration, volcanoes, and anthropogenic activities like afforestation and deforestation [14], altering both sources and sinks of carbon. Fast-paced development across the world, especially in urban centres, is leading to rapid transformation of the land cover and its use. Land cover and land use (LULC) changes caused by both natural and anthropogenic activities lead to changes in the carbon stock of urban centres, which further degrades ecosystem service functions [15]. Therefore, understanding land use dynamics and their effect on carbon sequestration capacity is vital for sustainable urban development [16].

Several methodologies have been employed to explore the relationship between land use dynamics and their effect on carbon storage capacity, such as field investigations [13,17] and remote sensing tools [18,19]. One of the earliest studies using a simulation model to understand the interaction between the C pools in the biosphere, atmosphere, and the ocean was done by Goudriaan J. [20]. Subsequently, various models have increasingly been used to simulate, project, and evaluate the consequences of urban sprawl on local C sequestration capacity at various spatial and temporal scales, such as DLEM (the Dynamic Land Ecosystem Model) [21], the CESVA model (Carbon Exchange in the Vegetation-Soil-Atmosphere System) [22], and the CASA (Carnegie Ames Stanford Application) productivity model [23], etc. In developed nations such as in Europe and North America, there are several works wherein records of urban vegetation and C stock have been estimated using other models like i-Tree Eco [24,25], CITYgreen [23,26], and the UFORE (Urban Forest Effects) model [27,28]. These freely available tools aid in the inventorisation of local flora and provide species-specific data. Such models make the estimation of the C storage of urban greens simpler and efficient, and are therefore widely used in urban areas. However, the applicability of these tools is limited for other geographical locations because of the considerable variation in the geography, climate, and vegetation types [29]. For developing countries like India, such modelling and assessment tools are unavailable and national forest inventories most often do not include urban trees [30]. Because of the lack of such city-scale inventories, most of the vegetation studies and C stock estimations are still dependent on field measurements and limited area inventory data [31–40].

Recently, the Integrated Valuation of Ecosystem Services and Tradeoffs-Carbon Storage and Sequestration (InVEST-CSS) model, started under the Natural Capital Project [41], has been used in several studies to ascertain the C storage capacity of urban areas based on land use/cover changes [42–47]. This CSS module of the model calculates the present amount of C stored and assesses the quantity of sequestered cover time for an area. This model offers a simple and authentic method of estimating C storage with minimum input parameters [48]. Polasky et al. (2011) [49] examined the effects of real and different scenarios of LULC on C-holding capacity in Minnesota, USA, from 1992 to 2001 using the InVEST model. They also suggested different strategies to manage land to enhance C-storage capacity. Leh et al. (2013) [50] also examined the effects of LULC on Ghana's C stock from 2000 to 2009 at the national level using the same tool. Delphin et al. (2013) [51] assessed the effects of hurricanes on the watersheds and forests of Florida and subsequent C loss. Liu et al.

(2018) [52] employed InVEST to study the fluctuation in C stock in northern Shaanxi at different scales. Abdo and Satyaprakash (2021) [53] analysed the consequences of LULC on C storage in Addis Ababa city, Ethiopia, from 1988 to 2018 and simulated it for 2028–2038 using InVEST. InVEST was also used to evaluate the C stored in the Jiroft plain, Iran, by Adelisardou et al. (2022) [54] and in Uva province in Sri Lanka by Piyathilake et al. (2022) [55]. The model has also been applied in other areas like Guilin, China, by He et al. (2023) [56], Nador, Morocco, by Rachid et al. (2024) [57] and Pakistan by Zafar et al. (2024) [58].

In India, there has been limited applicability and use of InVEST for the analysis of C storage capacity in natural landscapes and it has not been extended to urban areas. For example, Gupta et al. (2017) [59] studied the C storage in the Bhidalna microwatershed, Dehradun District of Uttarakhand state in India. The tool has also been used to analyse the dynamic pattern of C sequestration in the Periyar Tiger Reserve [60], Sariska Tiger Reserve [61], Sundarban Biosphere Reserve [62], and Askot Wildlife Sanctuary [63].

Therefore, the primary objectives of this study are to: (i) explore the spatio-temporal dynamics of the above- and below-ground C storage of an incessantly expanding urban centre in India-Noida from 2011 to 2019 using the InVEST-CSS model; (ii) forecast the amount that will be stored in the future year 2027, through the analysis of alterations in the land use over these years; and (iii) estimate the monetary cost of the observed variation in the C stock over the years. Urban soils are highly heterogeneous because of the presence of concrete, asphalt, metals, plastics, and many contaminants. Soil sealing with impermeable surfaces, such as roads and pavements, leads to a reduction in SOC content in urban areas [64–66]. Chien & Krumins (2022) [67] also reports that SOC in natural habitats is significantly higher than that of urban green spaces and urban intensive habitats. Therefore, this study is limited to the evaluation of above- and below-ground C only, despite SOC being an important contributor to the terrestrial carbon pool.

Correct estimates of the C stored in cities are very important to highlight and understand the function of UGS in the atmospheric C balance. To understand and better manage the mitigation potential of green spaces, verifiable and reasonable estimates of the C sequestered from cities are needed. The findings of this study will help urban planners and managers to better comprehend the land use dynamics, their drivers, and the subsequent effect on the C stocks of the city.

2. Study Location

This study is carried out in relation to Noida city, an abbreviation for the New Okhla Industrial Development Authority. It is situated in the district of Gautam Buddha Nagar in the state of Uttar Pradesh, in northern India (Figure 1).

Climate—Noida has a blisteringly hot and humid environment for a large portion of the year. The climate stays hot during the summer, i.e., from March to June, and the temperature ranges between 48 and 28 °C. Monsoon prevails from mid-June to mid-September with normal precipitation of 93.2 cm. Temperatures tumble down to as low as 3–4 °C at the peak of the winter due to the cold waves from the Himalayan region, which make the winters in Noida chilly and harsh. Noida additionally has haze and smog in winter, decreasing the overall visibility in the city.

Soil—Much of the land in Noida is not fertile and the agricultural yield is low. It is in the flood fields of the Yamuna River on one side and the Hindon River on the other and is situated on the old stream bed. Pedogenic material is mostly formed by sandy and loamy fluvisols [68] or fluverine alluvial soils [69] Wheat, rice, sugar cane, and millets are the primary crops planted in the area.

Vegetation—The vegetation in the space falls under the classification of the subtropical deciduous sort, although at present it does not have any extent of forest. Noida Authority has built up various forms of green spaces within the city like green belts, gardens, parks, avenue plantations, and vertical gardens. Every residential sector in the city has a park/playground, adding to the overall verdancy of Noida and providing respite to the Noida citizens. Approximately 10–12% of the land is allocated to parks, playgrounds, and other open spaces in each of the sector. The city authorities have also designed and developed several big green spaces for the benefit of the residents.

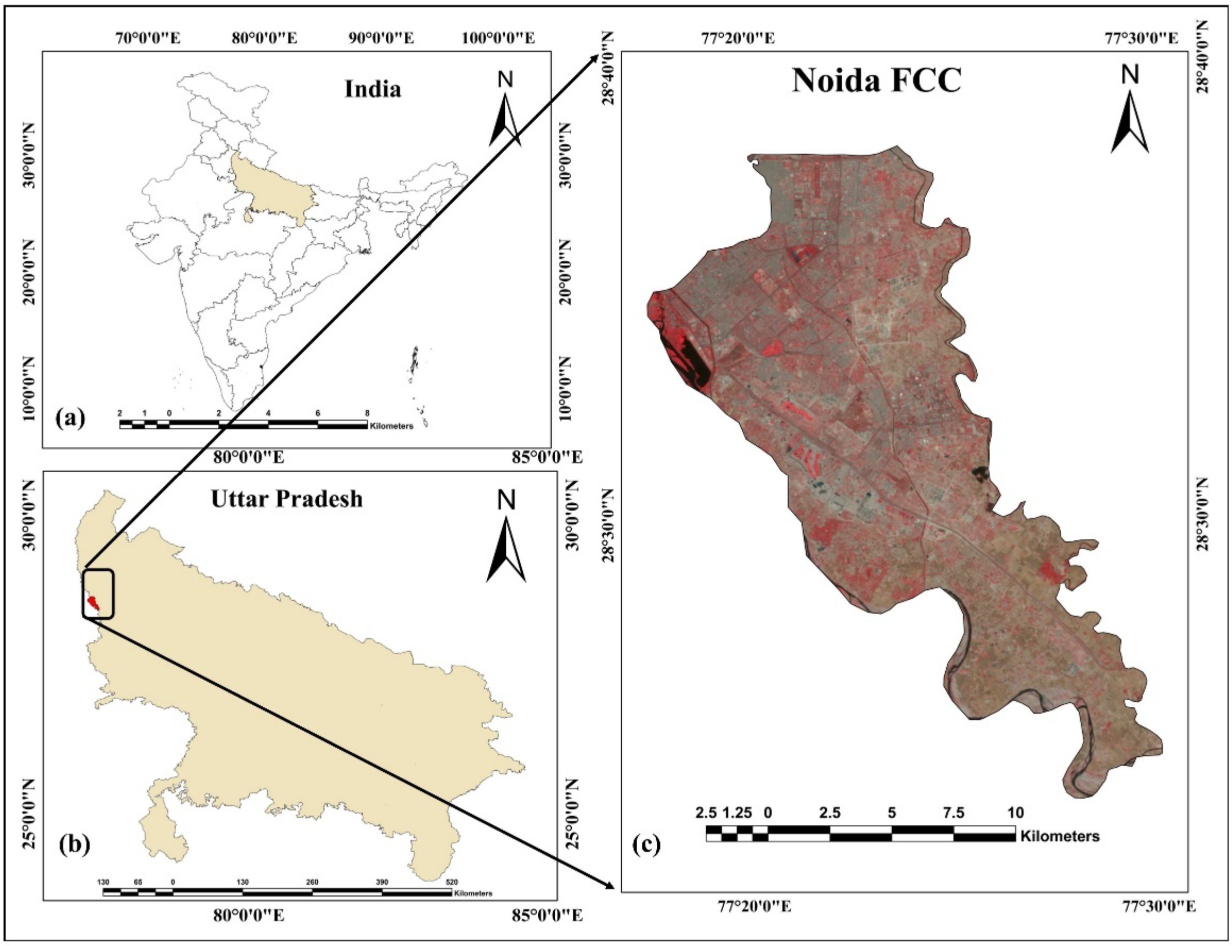

Figure 1. Study Location (**a**) Map of India; (**b**) Map of Uttar Pradesh; (**c**) Satellite Landsat 8 Image of Noida City.

Geomorphology—The landscape of this region is for the most part plain with a gentle incline fluctuating between 0.2 and 0.1 percent from north-east to south-west. The highest and lowest height ranges between 204 m and 195 m above the mean sea level (MSL) close to the villages Parthala Khanjarpur in the northeast and Garhi in the southwest, respectively. Most of Noida territory is under 200 m mean ocean level.

As a satellite city around the national capital, New Delhi, it harbours several multinational companies (MNCs) and industries. The city is burgeoning rapidly with rampant urbanisation and industrialisation. The presence of good infrastructure, educational facilities, employment opportunities, and modern residential spaces surrounded with greenery has attracted mass migration and unplanned growth in the city over the years. Extensive urbanisation started around 2010-11 in Noida, such as the construction of the Yamuna Expressway, the Indian motor racing circuit, the Rashtriya Dalit Prerna Sthal, the Green Garden, and several residential spaces. The Noida Master Plan 2011 which was revised in 2006 for the perspective year of 2021, also proposed a total of 14964 hectares of land for the development of urban activities.

An estimation of CSS at the local, regional, and landscape levels is crucial to assist India's nationally determined contributions (NDCs) to the United Nations Framework Convention on Climate Change (UNFCCC) [70]. The 'National Mission for a Green India', one of the sub-missions under the National Action Plan on Climate Change (NAPCC), has also identified priority research areas such as to study vegetation response to climate change and benchmarking the C-capture potential of ecosystems, etc. Noida is one of the largest planned cities in India; still, there are no accurate estimates of the C storage of the city. There is a paucity of work highlighting the contribution of spatio-temporal dynamics of land use and its carbon storage to mitigate urban CO_2 emissions in such Indian metropolitan cities. Therefore, Noida was taken as the study area for this study so that the analysis could be replicated to other urban agglomerations within and outside India.

3. Materials and Methods

The overall methodology of this study is illustrated in Figure 2 and detailed further below.

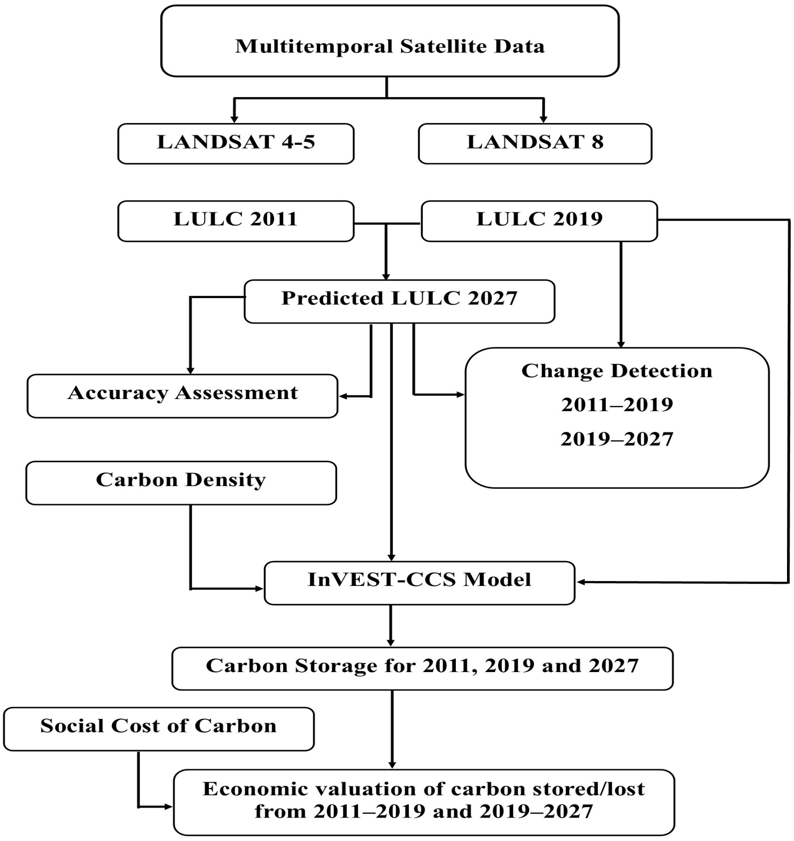

Figure 2. Overall Methodology.

3.1. Satellite Dataset and Software Used

Multi-temporal satellite imagery was retrieved from USGS (the United States Geological Survey) for two time periods—2011 and 2019. The details of the imagery employed for this study are as follows (Table 1). The following software were used for analysing satellite data—ERDAS Imagine 14, ArcGIS10.2, and Quantum GIS 2.18.

Table 1. Details of Satellite Imageries.

S. No.	Dataset	Retrieved on	Spatial Resolution	Retrieved from
1.	LANDSAT 5	22 April 2011	30 m	United States Geological Survey (USGS)
2.	LANDSAT 8	28 April 2019	30 m	

3.2. Derivation of Landuse and Landcover and Accuracy Assessment

LULC maps were prepared using Landsat Satellite data for the years 2011 and 2019, respectively. Google Earth Engine's Random Forest classification method was applied to delineate five LULC categories, viz., Built-up land, Vegetation, Agricultural/fallow land, Barren land, and Water bodies. Owing to its high accuracy and easy computation, RF has proven to be the first choice for the classification of urban landscapes [71] and was therefore used in preparing LULC in this study. The final step after the LULC classification is to conduct an accuracy evaluation to quantify the success of the method in correctly allocating pixels to the appropriate land cover classes.

The Google Earth Engine (GEE) is a cloud-based interface for the analysis of geospatial data, addressing the major issues related to the storage, processing, and analysis of immensely large datasets. The GEE library provides access to both types of classification techniques. A few of the supervised classification techniques are the support vector machine (SVM), random forest (RF), and the classifiers classification and regression tree (CART) [72]. Random Forest is a popular supervised classification method featured in GEE [73]. An RF model combines field measurements and remotely sensed data using multiple decision trees or 'the forest'. Also called the ensemble classifier, RF is a non-parametric classification algorithm. The most popular class is voted after each decision tree classifies the data independently.

3.3. Prediction of LULC of Future Years

LULC for the future year 2027 was simulated using MOLUSCE plugin in the QGIS software, which offers a user-friendly and intuitive plugin for users to perform modelling and simulation. In ArcMap, a set of spatial variables with the same picture element size, location, and fixed scale was created, including slope, aspect, and road. The whole set of data was then imported into the MOLUSCE Plugin, to generate an LULC map and determine the trend of change for the study. Annual percentage change in area was computed by the plugin and a transition grid illustrating the number of picture elements transforming to another LULC was displayed. It also created an area change map that illustrates the changes in the land from 2011 to 2019 and from 2019 to 2027. The LULC transition potential was modelled by MOLUSCE using Artificial Neural Network (ANN), Multi-Criteria Evaluation (MCE), Weights of Evidence (WOE), and Logistic Regression (LR) techniques. The ANN model was used in this study to simulate spatial LULC change because it is very good at capturing the complicated non-linear behaviour of ecosystems [74]. The plugin utilised a Cellular-Automata Simulation to predict the change in LULC. The input data used to model potential land use in 2027 was defined as the LULC maps from 2011 and 2019. This model was not based on any anthropogenic or natural processes, but rather on the past change.

3.4. Estimation of Carbon Storage

In this analysis, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST)—Carbon Storage and Sequestration (CSS) model developed by the Natural Capital Project [75] was employed to determine the carbon sequestration potential of Noida. Though SOC is a significant contributor to terrestrial C, this study only used AGB and BGB for the computation of C stored. Using the LULC maps generated in the previous steps and C density as the input, the CCS module of the model can calculate the total amount of C stored in the landscape. The carbon density of any vegetation is usually calculated by using the biomass and total C content coefficient, while the carbon density of the soil is obtained by considering the bulk density, organic matter content, and thickness of the soil [76]. Parameters like biomass, bulk density, organic matter content, and thickness of the soil are determined through field surveys and chemical analysis. The C densities of various LULC types in this study were determined using secondary data from FSI and IPCC [6,61,77,78]. The output consists of storage, sequestration, and aggregate totals, represented as Mg/pixel, and maps C storage densities to LULC maps. The total C sequestered or lost over time was also computed using the current and prospective LULC maps. The final step involved assessing the monetary value of C sequestration/loss over time, rather than storage, for each scenario. Three pieces of information were needed for this calculation: the annual discount rate, the monetary worth of each unit of C, and the evolution of the cost of C sequestration. The monetary value of a metric tonne of C sequestered was taken to be $86 with a 3% of market rate of discount, and zero change in the cost of C in a year [79].

4. Results and Discussion

4.1. Spatio-Temporal Analysis of Land Use and Land Cover

Understanding the dynamics of the altering landscape and making future predictions are made easier by the spatial and temporal analysis of the change in urban land cover. Both the satellite datasets from 2011 and 2019 underwent supervised classification using the appropriate training signatures for the major LU/LC classes, including built-up land, barren land, vegetation, waterbodies, and agriculture/fallow land. The results of the land use/land cover are given in Table 2 and the classified outputs are given in Figure 3.

Table 2. LULC Statistic—2011, 2019, and 2027.

LULC Classes	Year 2011		Year 2019		Year 2027		Change (2011–2019)		Change (2019–2027)	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Agricultural/ Fallow land	86.74	41.00	27.68	13.09	24.10	11.39	−59.06	−27.91	−3.58	−1.70
Barren land	13.84	6.55	12.84	6.07	14.30	6.76	−1.00	−0.48	1.46	0.69
Waterbodies	8.34	3.93	4.64	2.18	4.30	2.03	−3.70	−1.75	−0.34	−0.15
Built-up land	74.70	35.30	106.77	50.46	120.32	56.88	32.07	15.16	13.55	6.42
Vegetation	27.92	13.22	59.61	28.20	48.52	22.94	31.69	14.98	−11.09	−5.26
Total	211.54	100	211.54	100	211.54	100				

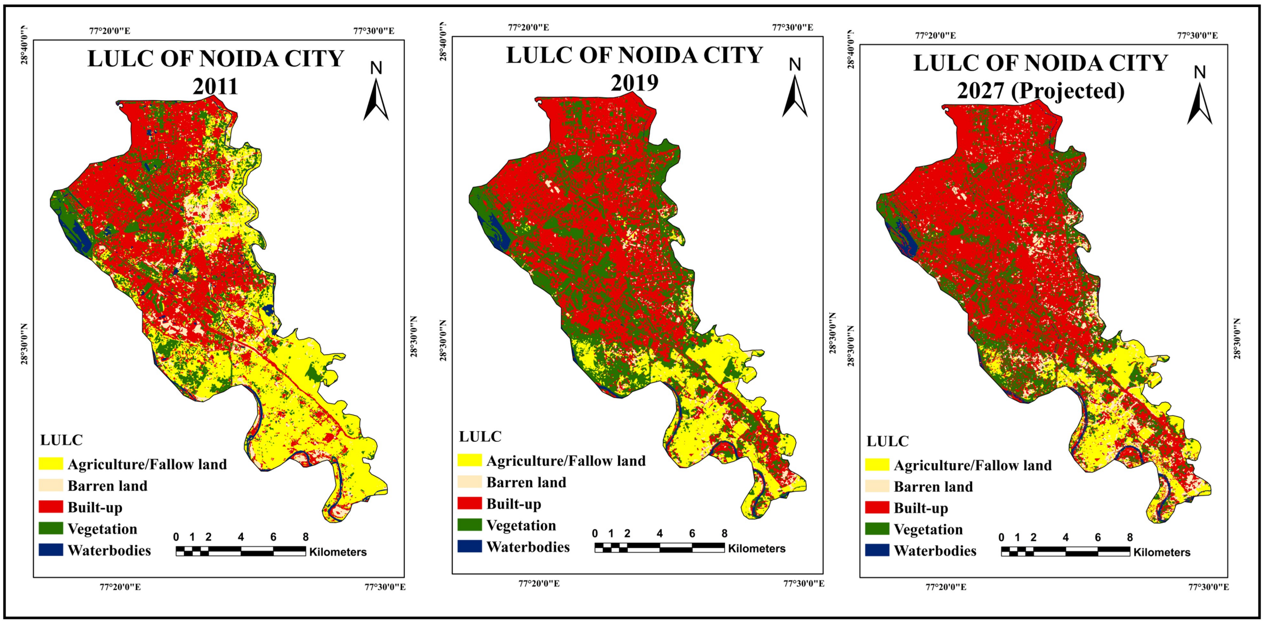

Figure 3. LULC of Noida City 2011, 2019 and 2027.

The classified map of 2011 shows a high concentration of built-up land in the north-western part and moderate density in the central part of Noida City. It is evident from the LULC of 2019 that the direction of the urban sprawl is extending further into the northeast and south of the city. It is to be noted that the area under vegetation and the built-up categories were 27.92 km^2 and 74.7 km^2, respectively, in 2011, which further increased to 59.61 km^2 and 106.77 km^2, respectively, in 2019. On the other hand, the agricultural/fallow land area, which was 86.74 km^2 in 2011, shrunk to 27.68 km^2 in 2019. The area under barren land and water body showed a marginal decrease in 2019. Thus, most of the increment in the built-up land came about because of the transformation of agricultural land into other land use classes, in which cultivated lands and other barren terrains were replaced by building, roads, pavements, and different infrastructures which likewise brought about the increment in urban vegetation as well.

For the simulated LULC of the year 2027, it can be observed that there will be a large increment in built-up land (6.42%) and a slight increase in barren land (0.69%). Such increment in the barren and built-up area can be attributed to future construction activities and the transformation of agricultural land, respectively. The prediction indicated that an additional area of 32.07 km^2 will be transformed into fallow land, whereas not much change is expected in waterbodies. However, agricultural/fallow land and vegetation will both decrease year after year, resulting in a potential loss by 2027. This method is based on past changes in pixels according to the LULC of 2011 and 2019. If the present trend persists, the majority of the other land cover classes will be replaced by built-up or barren land, as indicated by the projected land cover for 2027. The capacity for terrestrial C sequestration will further decrease because of the anticipated reduction in the area used for agriculture and urban vegetation.

4.2. Accuracy Assessment

An accuracy assessment verifies the accuracy of the pixel distribution and the viability of maximum likelihood in urban mapping. The final image had 92% overall accuracy in 2011 and 93% in 2019. The κ coefficient was 0.93 in 2011, followed by 0.89 in 2019 (Tables 3 and 4).

Table 3. Accuracy Assessment Error Matrix (2011).

<table>
<tr><th>Reference</th><th>Classes</th><th>Agricultural/ Fallow Land</th><th>Barren Land</th><th>Built-Up Land</th><th>Vegetation</th><th>Water Bodies</th><th>Row Total</th><th>Producer Accuracy (%)</th><th>User Accuracy (%)</th><th>Overall Accuracy (%)</th><th>κ Coefficient</th></tr>
<tr><td rowspan="6">Classified</td><td>Agricultural/ Fallow land</td><td>20</td><td>1</td><td>2</td><td>1</td><td>0</td><td>24</td><td>100.00</td><td>83.33</td><td rowspan="6">91.6667</td><td rowspan="6">0.93</td></tr>
<tr><td>Barren land</td><td>0</td><td>5</td><td>0</td><td>0</td><td>0</td><td>5</td><td>83.33</td><td>100.00</td></tr>
<tr><td>Built-up land</td><td>0</td><td>0</td><td>20</td><td>0</td><td>0</td><td>20</td><td>90.91</td><td>100.00</td></tr>
<tr><td>Vegetation</td><td>0</td><td>0</td><td>0</td><td>8</td><td>0</td><td>8</td><td>88.89</td><td>100.00</td></tr>
<tr><td>Water bodies</td><td>0</td><td>0</td><td>0</td><td>0</td><td>3</td><td>3</td><td>100.00</td><td>100.00</td></tr>
<tr><td>Column Total</td><td>20</td><td>6</td><td>22</td><td>9</td><td>3</td><td>60</td><td></td><td></td></tr>
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Table 4. Accuracy Assessment Error Matrix (2019).

<table>
<tr><th>Reference</th><th>Classes</th><th>Agricultural/ Fallow Land</th><th>Barren Land</th><th>Built-Up Land</th><th>Vegetation</th><th>Water Bodies</th><th>Row Total</th><th>Producer Accuracy (%)</th><th>User Accuracy (%)</th><th>Overall Accuracy (%)</th><th>κ Coefficient</th></tr>
<tr><td rowspan="6">Classified</td><td>Agriculture/ Fallow land</td><td>7</td><td>0</td><td>0</td><td>1</td><td>0</td><td>8</td><td>87.50</td><td>87.50</td><td rowspan="6">93.33</td><td rowspan="6">0.89</td></tr>
<tr><td>Barren land</td><td>0</td><td>8</td><td>1</td><td>0</td><td>0</td><td>9</td><td>88.89</td><td>88.89</td></tr>
<tr><td>Built-up land</td><td>0</td><td>1</td><td>24</td><td>0</td><td>0</td><td>25</td><td>96.00</td><td>96.00</td></tr>
<tr><td>Vegetation</td><td>1</td><td>0</td><td>0</td><td>15</td><td>0</td><td>16</td><td>93.75</td><td>93.75</td></tr>
<tr><td>Water bodies</td><td>0</td><td>0</td><td>0</td><td>0</td><td>2</td><td>2</td><td>100.00</td><td>100.00</td></tr>
<tr><td>Column total</td><td>8</td><td>9</td><td>25</td><td>16</td><td>2</td><td>60</td><td></td><td></td></tr>
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The κ statistic was used to determine the validation of the simulated LULC. The predicted LULC map's accuracy rate was 94.88 percent, with an overall κ of 0.92 and a κ histogram of 0.93 (Table 5).

Table 5. Validation of simulated LULC—2027.

Method	Correctness %	Overall κ	κ (Histogram)
Artificial Neural Network (ANN)	94.88	0.92	0.93

4.3. Impact of Land Use Change on C Storage

The C storage of the city was estimated using the InVEST (v. 3.11.0) software. The amount of C stored in every grid is calculated using LULC maps and the C density of every category of land use. As per Table 6, the C stored in vegetation is the maximum for all the years, followed by agricultural land in 2011 and built-up land in 2019 and 2027, respectively. For the year 2011, the C stored in vegetation is 234,499.39 metric tonnes (77.27%) followed by agricultural land with 43,176.27 metric tonnes (14.23%) and built-up land as 22,943.98 metric tonnes (7.56%), respectively. Subsequently in 2019, the overall C storage of the city increased by approximately 67% to 506,558.32 metric tonnes, distributed across built-up land, agricultural/fallow land, barren land, and vegetation. Though it is seen that a higher quantity of C is stored in the vegetation and built-up class, a drastic decrease in the C storage in agricultural classes is observed. A slight drop in C storage is observed in barren land in 2019. For the predicted year 2027, an overall C storage of 454,591.85 metric tonnes is recorded, highlighting a loss in C storage in the future. It is noteworthy that though the vegetation increased between 2011 and 2019, an increase in built-up and barren land, attributed to urbanisation, will potentially cause C loss in the city in the coming years. Li et al. (2002) [44] also reported a similar trend wherein the conversion of cultivated land to construction land was the main reason for the C storage loss in Changchun city in China.

Table 6. Carbon storage in each LULC year wise.

LULC	Carbon Density (t/ha)	Total Carbon (t)			C in Each LULC (%)			Change in Carbon (t)	
		2011	2019	2027	2011	2019	2027	2011–2019	2019–2027
Agricultural/fallow land	5	43,176.27	13,446.41	12,989.88	14.23	2.65	2.86	−29,729.87	−456.53
Barren land	2	2850.75	2269.44	3460.00	0.94	0.45	0.76	−581.32	1190.56
Waterbodies	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Built-up land	3	22,943.98	30,696.46	35,984.99	7.56	6.06	7.92	7752.48	5288.53
Vegetation	82.17	234,499.39	460,146.03	402,156.99	77.27	90.84	88.47	225,646.64	−57,989.04
Total		303,470.40	506,558.34	454,591.85				203,087.93	−51,966.48

4.4. Carbon Sequestration Map

The CCS module of the software condensed the findings into an output image that represented the dispensation of C storage in Noida. In addition, the findings demonstrated that the city of Noida, which encompasses an area of land measuring 21,154 hectares, is currently storing 506,558.34 metric tonnes of C, distributed across all land classes. Therefore, the C storage for Noida city is 23.95 t/ha. The results are compared with other cities all over the world (Table 7). The C stored is less for Noida city in comparison to several other cities across the world.

Table 7. Carbon storage in urban vegetation in various cities/countries.

S. No.	City/Country	Carbon Storage (t/ha)	References
1.	Bolzano, Italy	0.75	[27]
2.	Jersey City, US	5.02 ± 0.68	[28]
3.	New Delhi, India	4.65	[80]
4.	Cities in Middle Korea	4.70–7.20	[81]
5.	Barcelona, Spain	11.20	[82]
6.	Leipzig, Germany	11.81 ± 3.25	[83]
7.	West Africa	14.00	[84]
8.	Canada	20.83	[85]
9.	**Noida, India**	**3.95**	**Present work**
10.	Baltimore, US	25.28 ± 3.16	[28]
11.	Hangzhou, China	30.25	[86]
12.	Leicester, UK	31.60	[29]
13.	Karlsruhe, Germany	32.30	[87]
14.	Shenyang, China	33.22 ± 4.32	[88]
15.	Atlanta, US	35.74 ± 2.69	[28]
16.	Beijing, China	43.70 ± 6.65	[89]
17.	Tripura, India	45.41	[90]
18.	Sacramento, US	46.91 ± 22.64	[91]
19.	Kumasi, Ghana	111.00	[92]

For both the years 2011 and 2019, the above-ground C stored ranged from 0 to 5.30 metric tonnes per pixel while the below-ground C ranged from 0 to 2.08 metric tonnes per pixel (Figures 4 and 5). The total C stored per pixel ranged from 0 to 7.39 metric tonnes for 2011, 2019 and the future year 2027 (Figure 6).

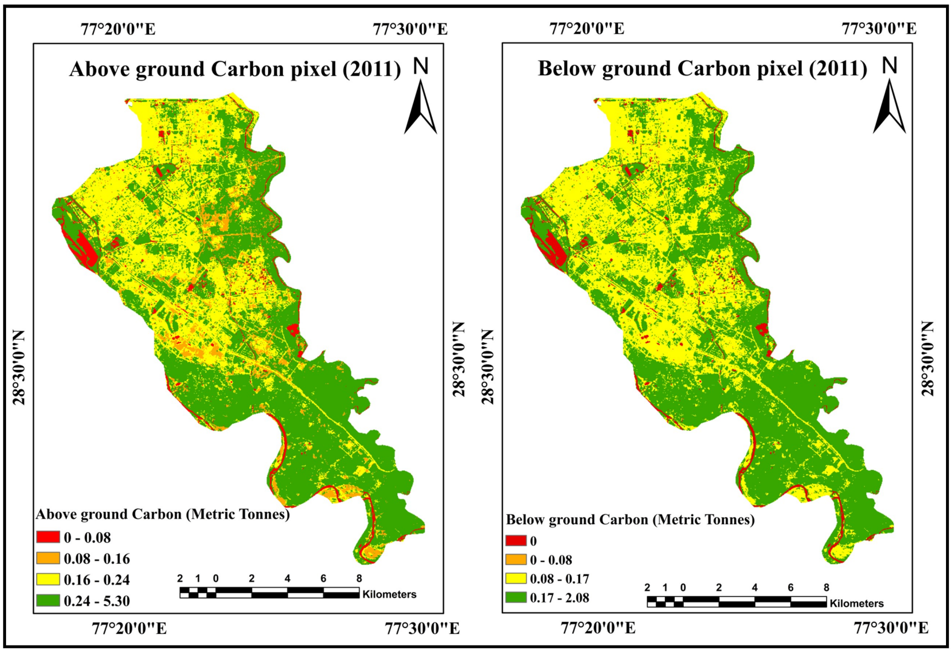

Figure 4. Above- and below-ground carbon per pixel (2011).

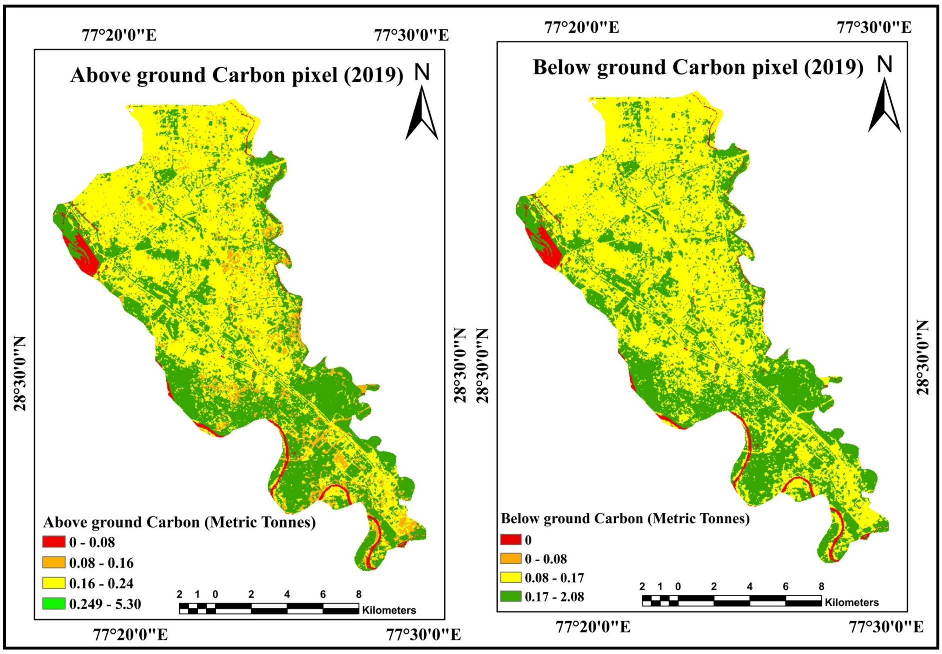

Figure 5. Above- and below-ground carbon per pixel (2019).

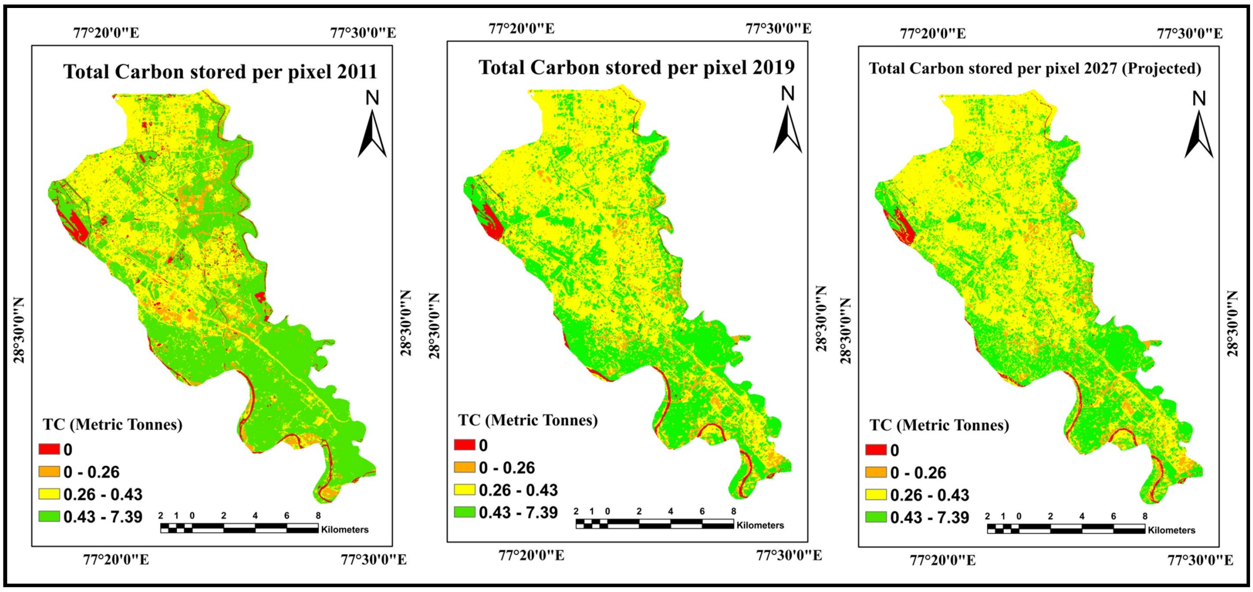

Figure 6. Total carbon stored per pixel (2011, 2019 and 2027).

The C stock per pixel is the same for all the three years and ranged from 0 to 7.39 metric tonnes. However, due to the transition in the LULC from one class to another class, the total C in each class changed for each year. The total C sequestered per pixel between 2011 to 2019 ranged from −7.39 to 7.39 and between 2019 and 2027, it ranged from −7.21 to 7.39 (Figure 7). Positive values indicate that C is being sequestered, while negative values indicate that C is being lost to the atmosphere. C sequestration is designated by positive values, whereas C loss to the atmosphere is implied by negative values.

If proper future urban planning and a substantial increment in green spaces are achieved, a higher C-storing capacity amidst built-up land, with a slightly lower percentage of C stored in vegetation and agriculture, can be achieved by the year 2027. The results obtained are corroborated by Jiang [93], who validated that reckless urbanisation in the Changsha-Zhuzhou-Xiangtan urban area has led to C storage loss as several green spaces and areas of agricultural land were transformed into built-up land. A study done for Addis

Ababa, Ethiopia, by Abdo and Satyaprakash (2021) [53] also stated that the conversion of most of the LULC classes into built-up land and transport will lead to a reduced area of green space in the city, causing a subsequent drop in C storage for the future simulated years 2028 and 2038.

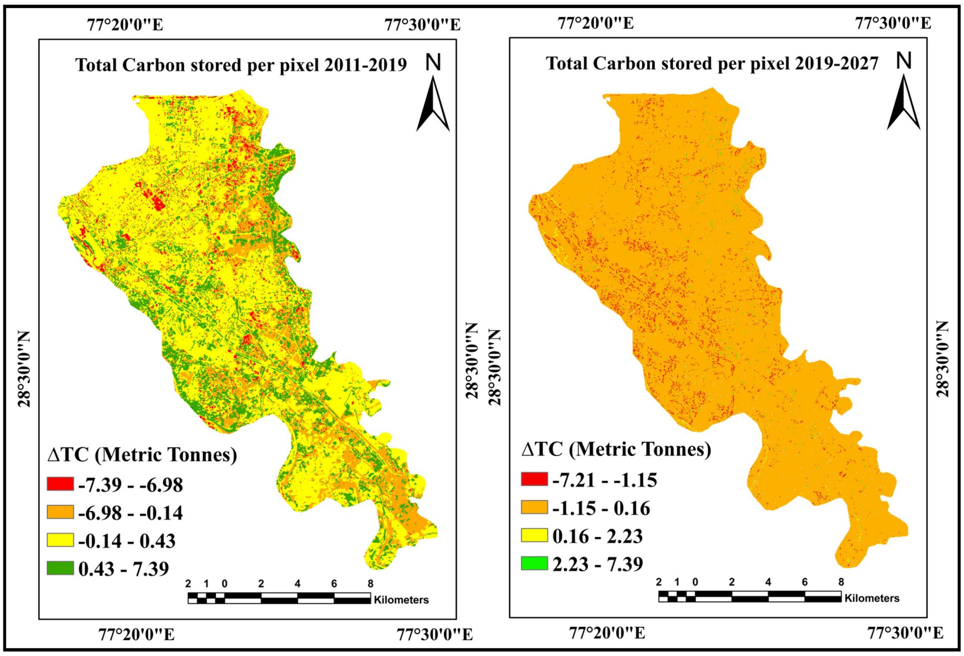

Figure 7. Total carbon stored per pixel—2011–2019 and 2019–2027.

4.5. Economic Valuation of Carbon Gain/Loss

The monetary contribution of C sequestered in the observed (2011–2019) and projected (2019–2027) time periods of Noida city are illustrated in Table 8. The findings reveal a monetary gain of 17.53 million dollars at a 3% discount rate due to C sequestered by urban green areas during the period 2011–2019 (Figure 8). Because of the augmentation in the C stock in the city from 2011 to 2019, this economic gain was observed. For the simulated period (2019–2027), a loss of 4.46 million dollars was recorded due to the predicted decline in vegetation (Figure 8). If the UGS of the city are not sustained and augmented, there will be a net loss of economic value derived from C stored. A similar study carried out in Jiroft plain, Iran, reported US$ 36 million as the cost of damage due to the loss of C stored between 2019 and 2045 [54].

Table 8. Total economic costs due to C sequestration.

Years	NPV (Million Dollars)
2011–2019	17.53
2019–2027	−4.46

4.6. Future Scope of the Work

This study could be further expanded by incorporating additional carbon pools such as Soil Organic Carbon (SOC) and dead organic matter, providing a more comprehensive carbon budget. Enhancing the model validation through field data integration and high-resolution remote sensing would improve the accuracy. Extending the temporal scope to include long-term projections and climate change scenarios would offer insights into sustainable urban planning. Integrating the findings with urban policies, developing decision support systems, and evaluating the socio-economic benefits of carbon sequestration could guide sustainable development. Additionally, using advanced machine learning models and real-time monitoring technologies would further refine the predictions and support urban sustainability efforts.

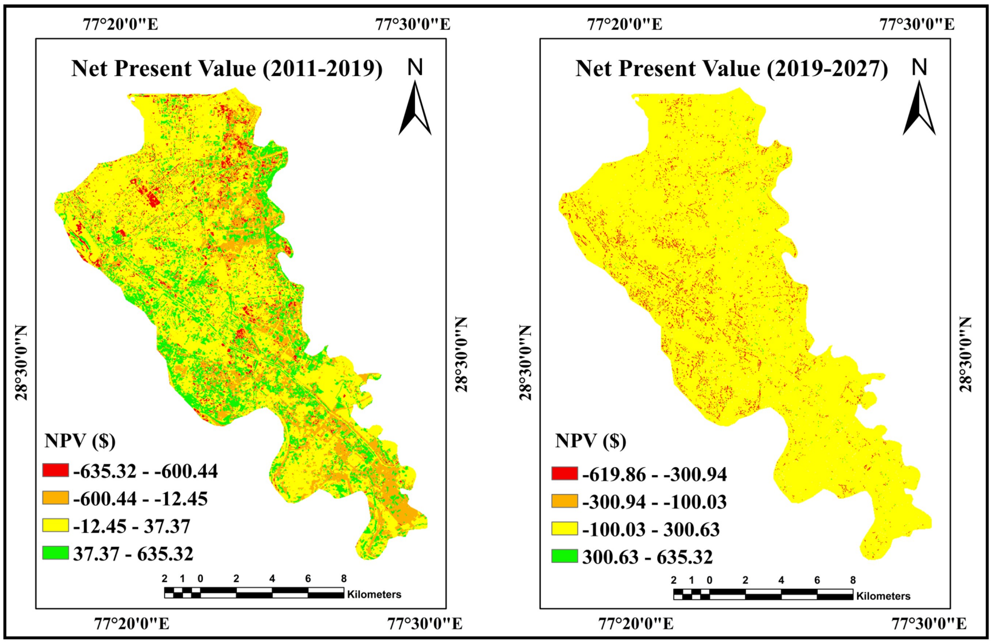

Figure 8. Net Present Value–2011–2019 and 2019–2027.

5. Conclusions

Economic development and government policies are the two primary propelling causes of the LULC changes observed in Noida. The overall direction of urban growth is towards the northeast and south of the city, along which the density has also increased in the northern part. Areas under built-up land and vegetation increased between 2011 and 2019, while agricultural areas decreased substantially. Over the past twenty years, the city has undergone rapid conurbation. As per the development plan for city for the year 2021, 6055 hectares of area were recommended for urban development, with 61.61 percent of the total land stated to have already been developed. The building of the Metro line, the Buddha International Circuit, the FNG and Yamuna Expressway, the National Dalit Memorial, as well as other residential and commercial buildings, are a few examples [94].

Since the InVEST model facilitated the simulation, forecast, and monetary evaluation of the possible impacts of urbanisation on the city's C-storage capacity at different levels, such models are becoming more and more popular. To assess current and future climatic consequences at the city scale, it is essential to comprehend the magnitude and spatio-temporal distribution of carbon dioxide (CO_2) equivalents. This study exemplifies a bottom-up approach or regional analyses, which can be replicated for all other urban cities experiencing significant landscape alterations. Estimates of the C storage of urban areas provide past records to serve as a baseline and a precursor to study future changes, and therefore, more such city-scale analyses are required rather than just depending on the national estimates. The monetary valuation of ecosystem services like C sequestration by urban green areas helps us to comprehend the social and environmental importance of these functions of nature. The estimation and mapping of the changing pattern of the C sequestration potential of urban green spaces is a crucial tool that can aid in devising prudent management strategies of urban green spaces, augmenting cities' capacities to store C and manage climate change.

The findings of this study highlight a momentous transformation of the land cover in the city, and if appropriate actions are not taken as soon as possible, this could result in the elimination of all available space for vegetation. This would, as a result of a decrease in C sequestration, further exacerbate a variety of environmental, socioeconomic, and public health issues, and would also prevent the city from growing in a sustainable way. As a result, those responsible for formulating public policy and urban planning should collaborate to determine how land should be utilised for future sustainable urban development. Such key data about the amount and distribution of C stored within existing urban vegetation, the portion of C sequestered or lost over time, and its relationship with the changing urban landscape are vital for such decisions.

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References

1. Zhuang, Q.; Shao, Z.; Gong, J.; Li, D.; Huang, X.; Zhang, Y.; Xiaodi, X.; Dang, C.; Chen, J.; Altan, O.; et al. Modeling Carbon Storage in Urban Vegetation: Progress, Challenges, and Opportunities. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *114*, 103058. [CrossRef]
2. Allen, C.; Metternicht, G.; Wiedmann, T. National Pathways to the Sustainable Development Goals (SDGs): A Comparative Review of Scenario Modelling Tools. *Environ. Sci. Policy* **2016**, *66*, 199–207. [CrossRef]
3. IPCC. *IPCC on Mitigation of Climate Change*; Cambridge University Press: Cambridge, UK, 2014.
4. Gurney, K.R.; Liang, J.; Roest, G.; Song, Y.; Mueller, K.; Lauvaux, T. Under-reporting of Greenhouse Gas Emissions in US Cities. *Nat. Commun.* **2021**, *12*, 553. [CrossRef]
5. Kinnunen, A.; Talvitie, I.; Ottelin, J.; Heinonen, J.; Junnila, S. Carbon Sequestration and Storage Potential of Urban Residential Environment–A Review. *Sustain. Cities Soc.* **2022**, *84*, 104027. [CrossRef]
6. IPCC. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*; Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K., Eds.; National Greenhouse Gas Inventories Programme, IGES: Tokyo, Japan, 2006; pp. 1–20.
7. Scharlemann, J.P.; Tanner, E.V.; Hiederer, R.; Kapos, V. Global Soil Carbon: Understanding and Managing the Largest Terrestrial Carbon Pool. *Carbon Manag.* **2014**, *5*, 81–91. [CrossRef]
8. Vashum, K.T.; Jayakumar, S. Methods to Estimate Above-Ground Biomass and Carbon Stock in Natural Forests—A Review. *J. Ecosyst. Ecogr.* **2012**, *2*, 116. [CrossRef]
9. Helen, J.M.; Gasparatos, A. Land Use Change, Carbon Stocks and Tree Species Diversity in Green Spaces of a Secondary City in Myanmar, Pyin Oo Lwin. *PLoS ONE* **2019**, *14*, e0225331. [CrossRef]
10. Behera, S.K.; Mishra, S.; Sahu, N.; Manika, N.; Singh, S.N.; Anto, S.; Kumar, R.; Husain, R.; Verma, A.K.; Pandey, N. Assessment of Carbon Sequestration Potential of Tropical Tree Species for Urban Forestry in India. *Ecol. Eng.* **2022**, *181*, 106692. [CrossRef]
11. Shadman, S.; Khalid, P.A.; Hanafiah, M.M.; Koyande, A.K.; Islam, M.A.; Bhuiyan, S.A.; Woon, K.S.; Show, P.L. The Carbon Sequestration Potential of Urban Public Parks of Densely Populated Cities to Improve Environmental Sustainability. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102064. [CrossRef]
12. Uniyal, S.; Purohit, S.; Chaurasia, K.; Rao, S.S.; Amminedu, E. Quantification of Carbon Sequestration by Urban Forest Using Landsat 8 OLI and Machine Learning Algorithms in Jodhpur, India. *Urban For. Urban Green.* **2022**, *67*, 127445. [CrossRef]
13. Ren, Z.; Zheng, H.; He, X.; Zhang, D.; Shen, G.; Zhai, C. Changes in Spatio-Temporal Patterns of Urban Forest and Its Above-Ground Carbon Storage: Implication for Urban CO2 Emissions Mitigation under China's Rapid Urban Expansion and Greening. *Environ. Int.* **2019**, *129*, 438–450. [CrossRef]
14. Crisp, D.; Dolman, H.; Tanhua, T.; McKinley, G.A.; Hauck, J.; Bastos, A.; Sitch, S.; Eggleston, S.; Aich, V. How Well Do We Understand the Land-Ocean-Atmosphere Carbon Cycle? *Rev. Geophys.* **2022**, *60*, e2021RG000736. [CrossRef]
15. Zhang, F.; Xu, N.; Wang, C.; Wu, F.; Chu, X. Effects of Land Use and Land Cover Change on Carbon Sequestration and Adaptive Management in Shanghai, China. *Phys. Chem. Earth, Parts A/B/C* **2020**, *120*, 102948. [CrossRef]
16. Chen, Y.; Yue, W.; Liu, X.; Zhang, L.; Chen, Y. Multi-Scenario Simulation for the Consequence of Urban Expansion on Carbon Storage: A Comparative Study in Central Asian Republics. *Land* **2021**, *10*, 608. [CrossRef]
17. Tang, X.; Zhao, X.; Bai, Y.; Tang, Z.; Wang, W.; Zhao, Y.; Wan, H.; Xie, Z.; Shi, X.; Wu, B. Carbon Pools in China's Terrestrial Ecosystems: New Estimates Based on an Intensive Field Survey. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 4021–4026. [CrossRef]
18. Raciti, S.M.; Hutyra, L.R.; Newell, J.D. Mapping Carbon Storage in Urban Trees with Multi-Source Remote Sensing Data: Relationships between Biomass, Land Use, and Demographics in Boston Neighborhoods. *Sci. Total Environ.* **2014**, *500*, 72–83. [CrossRef]

19. Myeong, S.; Nowak, D.J.; Duggin, M.J. A Temporal Analysis of Urban Forest Carbon Storage Using Remote Sensing. *Remote Sens. Environ.* **2006**, *101*, 277–282. [CrossRef]
20. Goudriaan, J. Atmospheric CO_2, Global Carbon Fluxes and the Biosphere. In *Theoretical Production Ecology: Reflections and Prospects*; Pudoc: Wageningen, The Netherlands, 1990; pp. 17–40.
21. Zhang, C.; Tian, H.; Chen, G.; Chappelka, A.; Xu, X.; Ren, W.; Hui, D.; Liu, M.; Lu, C.; Pan, S.; et al. Impacts of Urbanization on Carbon Balance in Terrestrial Ecosystems of the Southern United States. *Environ. Pollut.* **2012**, *164*, 89–101. [CrossRef] [PubMed]
22. Gao, Z.Q.; Liu, J.Y.; Cao, M.K.; Li, K.R.; Tao, B. Impacts of Land-Use and Climate Changes on Ecosystem Productivity and Carbon Cycle in the Cropping-Grazing Transitional Zone in China. *Sci. China Ser. D-Earth Sci.* **2005**, *48*, 1479–1491. [CrossRef]
23. Yu, X.; Wang, H.; Cai, W.; Han, Y. Analysis of Urban Forest Carbon Sequestration Capacity: A Case Study of Zengdu, Suizhou. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2017**, *42*, W7. [CrossRef]
24. Ma, J.; Li, X.; Baoquan, J.; Liu, X.; Li, T.; Zhang, W.; Liu, W. Spatial Variation Analysis of Urban Forest Vegetation Carbon Storage and Sequestration in Built-Up Areas of Beijing Based on i-Tree Eco and Kriging. *Urban For. Urban Green.* **2021**, *66*, 127413. [CrossRef]
25. Song, P.; Kim, G.; Mayer, A.; He, R.; Tian, G. Assessing the Ecosystem Services of Various Types of Urban Green Spaces Based on i-Tree Eco. *Sustainability* **2020**, *12*, 1630. [CrossRef]
26. Li, Q.; Zhu, Y.; Zhu, Z. Calculation and Optimization of the Carbon Sink Benefits of Green Space Plants in Residential Areas: A Case Study of Suojin Village in Nanjing. *Sustainability* **2023**, *15*, 607. [CrossRef]
27. Russo, A.; Escobedo, F.J.; Timilsina, N.; Schmitt, A.O.; Varela, S.; Zerbe, S. Assessing Urban Tree Carbon Storage and Sequestration in Bolzano, Italy. *Int. J. Biodivers. Sci. Ecosyst. Serv. Manag.* **2014**, *10*, 54–70. [CrossRef]
28. Nowak, D.J.; Crane, D.E. Carbon Storage and Sequestration by Urban Trees in the USA. *Environ. Pollut.* **2002**, *116*, 381–389. [CrossRef]
29. Davies, Z.G.; Edmondson, J.L.; Heinemeyer, A.; Leake, J.R.; Gaston, K.J. Mapping an Urban Ecosystem Service: Quantifying Above-Ground Carbon Storage at a City-Wide Scale. *J. Appl. Ecol.* **2011**, *48*, 1125–1134. [CrossRef]
30. Vorster, A.G.; Evangelista, P.H.; Stovall, A.E.; Ex, S. Variability and Uncertainty in Forest Biomass Estimates from the Tree to Landscape Scale: The Role of Allometric Equations. *Carbon Balance Manag.* **2020**, *15*, 8. [CrossRef] [PubMed]
31. Vijayalaxmi, R.S.; Dnyanesh, M.M. Carbon Sequestration Potential of Urban Green Spaces (PMC Gardens) in Pune City, India. *J. Geogr. Environ. Earth Sci. Int.* **2021**, *25*, 22–38. [CrossRef]
32. Lahoti, S.; Lahoti, A.; Joshi, R.K.; Saito, O. Vegetation Structure, Species Composition, and Carbon Sink Potential of Urban Green Spaces in Nagpur City, India. *Land* **2020**, *9*, 107. [CrossRef]
33. Subba, M.; Pala, N.A.; Shukla, G.; Chakravarty, S. Study of the Variability of Home Gardens Influencing Carbon Stock under Sub-Humid Tropical Zone of West Bengal, India. *Indian For.* **2018**, *144*, 60–66.
34. Devi, R. Carbon Storage by Trees in Urban Parks: A Case Study of Jammu, Jammu and Kashmir, India. *Int. J. Adv. Res. Dev.* **2017**, *2*, 250–253.
35. Prabhakar, B.S.; Kumar, M.; Nandini, N. Evaluating the Tree Species Composition and Carbon Sequestration Potential of a Park in Bengaluru. *Int. J. Curr. Res.* **2015**, *7*, 22320–22325.
36. Tripathi, M.; Joshi, H. Carbon Flow in Delhi Urban Forest Ecosystems. *Ann. Biol. Res.* **2015**, *6*, 13–17.
37. Pandya, I.Y.; Salvi, H.; Chahar, O.; Vaghela, N. Quantitative Analysis on Carbon Storage of 25 Valuable Tree Species of Gujarat, Incredible India. *Indian J. Sci. Res.* **2013**, *4*, 137–141.
38. Kiran, G.S.; Kinnary, S. Carbon Sequestration by Urban Trees on Roadsides of Vadodara City. *Int. J. Eng. Sci. Technol.* **2011**, *3*, 3066–3070.
39. Nagendra, H.; Gopal, D. Street Trees in Bangalore: Density, Diversity, Composition and Distribution. *Urban For. Urban Green.* **2010**, *9*, 129–137. [CrossRef]
40. Waran, A.; Patwardhan, A. Urban Carbon Burden of Pune City: A Case Study from India. Master's Thesis, University of Pune, Pune, India, 2001.
41. Sharp, R.; Tallis, H.T.; Ricketts, T.; Guerry, A.D.; Wood, S.A.; Chaplin-Kramer, R.; Nelson, E.; Ennaanay, D.; Wolny, S.; Olwero, N.; et al. *InVEST 3.2.0 User's Guide*; The Natural Capital Project: Stanford, CA, USA, 2015.
42. Kohestani, N.; Rastgar, S.; Heydari, G.; Jouibary, S.S.; Amirnejad, H. Spatiotemporal Modeling of the Value of Carbon Sequestration under Changing Land Use/Land Cover Using InVEST Model: A Case Study of Nour-rud Watershed, Northern Iran. *Environ. Dev. Sustain.* **2023**, *26*, 14477–14505. [CrossRef]
43. Felix, N.B.; Campos, P.C.D.O.; Paz, I.; Marques, M.E.S. Geoprocessing Applied to the Assessment of Carbon Storage and Sequestration in a Brazilian Medium-Sized City. *Sustainability* **2022**, *14*, 8761. [CrossRef]
44. Li, Y.; Liu, Z.; Li, S.; Li, X. Multi-Scenario Simulation Analysis of Land Use and Carbon Storage Changes in Changchun City Based on FLUS and InVEST Model. *Land* **2022**, *11*, 647. [CrossRef]
45. Tao, Y.; Li, F.; Liu, X.; Zhao, D.; Sun, X.; Xu, L. Variation in Ecosystem Services across an Urbanization Gradient: A Study of Terrestrial Carbon Stocks from Changzhou, China. *Ecol. Modell.* **2015**, *318*, 210–216. [CrossRef]
46. Goldstein, J.H.; Caldarone, G.; Duarte, T.K.; Ennaanay, D.; Hannahs, N.; Mendoza, G.; Polasky, S.; Wolny, S.; Daily, G.C. Integrating Ecosystem-Service Tradeoffs into Land-Use Decisions. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 7565–7570. [CrossRef]

47. Nelson, E.; Sander, H.; Hawthorne, P.; Conte, M.; Ennaanay, D.; Wolny, S.; Manson, S.; Polasky, S. Projecting Global Land-Use Change and Its Effect on Ecosystem Service Provision and Biodiversity with Simple Models. *PLoS ONE* **2010**, *5*, e14327. [CrossRef] [PubMed]
48. He, C.; Zhang, D.; Huang, Q.; Zhao, Y. Assessing the Potential Impacts of Urban Expansion on Regional Carbon Storage by Linking the LUSD-Urban and InVEST Models. *Environ. Modell. Softw.* **2016**, *75*, 44–58. [CrossRef]
49. Polasky, S.; Nelson, E.; Pennington, D.; Johnson, K.A. The Impact of Land-Use Change on Ecosystem Services, Biodiversity, and Returns to Landowners: A Case Study in the State of Minnesota. *Environ. Resour. Econ.* **2011**, *48*, 219–242. [CrossRef]
50. Leh, M.D.K.; Matlock, M.D.; Cummings, E.C.; Nalley, L.L. Quantifying and Mapping Multiple Ecosystem Services Change in West Africa. *Agric. Ecosyst. Environ.* **2013**, *165*, 6–18. [CrossRef]
51. Delphin, S.; Escobedo, F.J.; Abd-Elrahman, A.; Cropper, W., Jr. Mapping Potential Carbon and Timber Losses from Hurricanes Using a Decision Tree and Ecosystem Services Driver Model. *J. Environ. Manag.* **2013**, *129*, 599–607. [CrossRef]
52. Liu, S.; Hu, N.; Zhang, J.; Lv, Z. Spatiotemporal Change of Carbon Storage in the Loess Plateau of Northern Shaanxi, Based on the InVEST Model. *Sci. Cold Arid Reg.* **2018**, *10*, 240–250.
53. Abdo, Z.A.; Satyaprakash. Modeling Urban Dynamics and Carbon Sequestration in Addis Ababa, Ethiopia, Using Satellite Images. *Arab. J. Geosci.* **2021**, *14*, 445. [CrossRef]
54. Adelisardou, F.; Zhao, W.; Chow, R.; Mederly, P.; Minkina, T.; Schou, J.S. Spatiotemporal Change Detection of Carbon Storage and Sequestration in an Arid Ecosystem by Integrating Google Earth Engine and InVEST (the Jiroft Plain, Iran). *Int. J. Environ. Sci. Technol.* **2022**, *19*, 5929–5944. [CrossRef]
55. Piyathilake, I.D.U.H.; Udayakumara, E.P.N.; Ranaweera, L.V.; Gunatilake, S.K. Modeling Predictive Assessment of Carbon Storage Using InVEST Model in Uva Province, Sri Lanka. *Model. Earth Syst. Environ.* **2022**, *8*, 2213–2223. [CrossRef]
56. He, Y.; Ma, J.; Zhang, C.; Yang, H. Spatio-temporal evolution and prediction of carbon storage in Guilin based on FLUS and InVEST models. *Remote Sens.* **2023**, *15*, 1445. [CrossRef]
57. Rachid, L.; Elmostafa, A.; Mehdi, M.; Hassan, R. Assessing carbon storage and sequestration benefits of urban greening in Nador City, Morocco, utilizing GIS and the InVEST model. *Sustain. Futures* **2024**, *7*, 100171. [CrossRef]
58. Zafar, Z.; Zubair, M.; Zha, Y.; Mehmood, M.S.; Rehman, A.; Fahd, S.; Nadeem, A.A. Predictive modeling of regional carbon storage dynamics in response to land use/land cover changes: An InVEST-based analysis. *Ecol. Inform.* **2024**, *82*, 102701. [CrossRef]
59. Gupta, S.; Nainwal, A.; Anand, S.; Singh, S. Valuation of Carbon Sequestration in Bidhalna Microwatershed, Uttarakhand, India Using InVEST Model. *Int. J. Adv. Earth Environ. Sci.* **2017**, *5*, 10–15.
60. Chacko, S.; Ravichandran, C.; Vairavel, S.; Mathew, J. Employing Measures of Spatial Distribution of Carbon Storage in Periyar Tiger Reserve, Southern Western Ghats, India. *J. Geovis. Spat. Anal.* **2019**, *3*, 1. [CrossRef]
61. Babbar, D.; Areendran, G.; Sahana, M.; Sarma, K.; Raj, K.; Sivadas, A. Assessment and Prediction of Carbon Sequestration Using Markov Chain and InVEST Model in Sariska Tiger Reserve, India. *J. Clean. Prod.* **2021**, *278*, 123–333. [CrossRef]
62. Bera, B.; Bhattacharjee, S.; Sengupta, N.; Shit, P.K.; Adhikary, P.P.; Sengupta, D.; Saha, S. Significant Reduction of Carbon Stocks and Changes of Ecosystem Service Valuation of Indian Sundarban. *Sci. Rep.* **2022**, *12*, 7809. [CrossRef]
63. Verma, P.; Siddiqui, A.R.; Mourya, N.K.; Devi, A.R. Forest carbon sequestration mapping and economic quantification infusing MLPnn-Markov Chain and InVEST carbon model in askot wildlife sanctuary, Western Himalaya. *Ecol. Inform.* **2024**, *79*, 102428. [CrossRef]
64. Wei, Z.; Wu, S.; Yan, X.; Zhou, S. Density and stability of soil organic carbon beneath impervious surfaces in urban areas. *PLoS ONE* **2014**, *9*, e109380. [CrossRef]
65. Piotrowska-Długosz, A.; Charzyński, P. The impact of the soil sealing degree on microbial biomass, enzymatic activity, and physicochemical properties in the Ekranic Technosols of Toruń (Poland). *J. Soils Sediments* **2015**, *15*, 47–59. [CrossRef]
66. Vasenev, V.I.; Van Oudenhoven, A.P.E.; Romzaykina, O.N.; Hajiaghaeva, R.A. The Ecological Functions and Ecosystem Services of Urban and Technogenic Soils: From Theory to Practice (A Review). *Eurasian Soil Sci.* **2018**, *51*, 1119–1132. [CrossRef]
67. Chien, S.C.; Krumins, J.A. Natural versus urban global soil organic carbon stocks: A meta-analysis. *Sci. Total Environ.* **2022**, *807*, 150999. [CrossRef]
68. WRB. 2022. Available online: https://wrb.isric.org/files/WRB_fourth_edition_2022-12-18.pdf (accessed on 10 August 2024).
69. Mishra, B.B. Indian System of Soil Classification: A way Forward. *Agric. Res. Technol. Open Access J.* **2016**, *3*, 555606. [CrossRef]
70. Brahma, B.; Nath, A.J.; Deb, C.; Sileshi, G.W.; Sahoo, U.K.; Das, A.K. A Critical Review of Forest Biomass Estimation Equations in India. *Trees For. People* **2021**, *5*, 100098. [CrossRef]
71. Ghosh, A.; Sharma, R.; Joshi, P.K. Random Forest Classification of Urban Landscape Using Landsat Archive and Ancillary Data: Combining Seasonal Maps with Decision Level Fusion. *Appl. Geogr.* **2014**, *48*, 31–41. [CrossRef]
72. Amani, M.; Ghorbanian, A.; Ahmadi, S.A.; Kakooei, M.; Moghimi, A.; Mirmazloumi, S.M.; Brisco, B. Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 5326–5350. [CrossRef]
73. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
74. Kumari, M.; Sarma, K.; Sharma, R. Predicting Spatial and Decadal LULC Changes in the Singrauli District of Madhya Pradesh Through Artificial Neural Network Models Using Geospatial Technology. *J. Indian Soc. Remote Sens.* **2022**, *51*, 519–530. [CrossRef]
75. Tallis, H.T.; Ricketts, T.; Guerry, A.D.; Wood, S.A.; Sharp, R.; Nelson, E.; Ennaanay, D.; Wolny, S.; Olwero, N.; Vigerstol, K.; et al. *InVEST 2.6.0 User's Guide*; The Natural Capital Project: Stanford, CA, USA, 2013.

76. Xu, L.; Zhang, J.; Hu, P.; Zhang, W.; Xiao, L.; Ye, Y.; Xiao, D.; Zhao, J.; Xiao, J.; Wang, K. Bedrock outcrops weakly promote rather than inhibit soil carbon sequestration after vegetation restoration. *Sci. Total Environ.* **2023**, *858*, 159470. [CrossRef]
77. Forest Survey of India (FSI). *Carbon Stock in India's Forests*; Ministry of Environment, Forest & Climate Change, Government of India: Dehradun, India, 2011.
78. Forest Survey of India (FSI). *India State of Forest Report*; Ministry of Environment, Forest & Climate Change, Government of India: Dehradun, India, 2019.
79. Ricke, K.; Drouet, L.; Caldeira, K.; Tavoni, M. Country-Level Social Cost of Carbon. *Nat. Clim. Chang.* **2018**, *8*, 895–900. [CrossRef]
80. Kaur, S.; Babbar, D.; Sarif, O.; Ghatak, A.; Jaafari, A. Assessment of carbon sequestration using InVEST model in Delhi, India. In *Conservation, Management and Monitoring of Forest Resources in India*; Springer International Publishing: Cham, Switzerland, 2022; pp. 33–56.
81. Jo, H.K. Impacts of Urban Greenspace on Offsetting Carbon Emissions for Middle Korea. *J. Environ. Manag.* **2002**, *64*, 115–126. [CrossRef] [PubMed]
82. Chaparro, L.; Terradas, J. *Ecological Services of Urban Forest in Barcelona*; Institut Municipal de Parcs i Jardins Ajuntament de Barcelona, Àrea de Medi Ambient: Barcelona, Spain, 2009.
83. Strohbach, M.W.; Haase, D. Above-Ground Carbon Storage by Urban Trees in Leipzig, Germany: Analysis of Patterns in a European City. *Landsc. Urban Plan.* **2012**, *104*, 95–104. [CrossRef]
84. Skole, D.L.; Samek, J.H.; Dieng, M.; Mbow, C. The Contribution of Trees Outside of Forests to Landscape Carbon and Climate Change Mitigation in West Africa. *Forests* **2021**, *12*, 1652. [CrossRef]
85. Pasher, J.; McGovern, M.; Khoury, M.; Duffe, J. Assessing Carbon Storage and Sequestration by Canada's Urban Forests Using High Resolution Earth Observation Data. *Urban For. Urban Green.* **2014**, *13*, 484–494. [CrossRef]
86. Zhao, M.; Kong, Z.H.; Escobedo, F.J.; Gao, J. Impacts of Urban Forests on Offsetting Carbon Emissions from Industrial Energy Use in Hangzhou, China. *J. Environ. Manag.* **2010**, *91*, 807–814. [CrossRef] [PubMed]
87. Kändler, G.; Adler, P.; Hellbach, A. Wie viel Kohlenstoff speichern Stadtbäume? Eine Fallstudie am Beispiel der Stadt Karlsruhe [How Much Carbon Is Stored by Urban Trees? A Case Study from the City of Karlsruhe]. *FVA-Einblick* **2011**, *2*, 7–10. (In German)
88. Liu, C.; Li, X. Carbon Storage and Sequestration by Urban Forests in Shenyang, China. *Urban For. Urban Green.* **2012**, *11*, 121–128. [CrossRef]
89. Yang, J.; McBride, J.; Zhou, J.; Sun, Z. The Urban Forest in Beijing and Its Role in Air Pollution Reduction. *Urban For. Urban Green.* **2005**, *3*, 65–78. [CrossRef]
90. Majumdar, T.; Selvan, T. Carbon Storage in Trees of Urban and Peri-Urban Forests of Agartala, Tripura. *IAETSD J. Adv. Res. Appl. Sci.* **2018**, *5*, 715–731.
91. McPherson, E.G.; Xiao, Q.F.; Aguaron, E. A New Approach to Quantify and Map Carbon Stored, Sequestered and Emissions Avoided by Urban Forests. *Landsc. Urban Plan.* **2013**, *120*, 70–84. [CrossRef]
92. Nero, B.F.; Callo-Concha, D.; Anning, A.; Denich, M. Urban Green Spaces Enhance Climate Change Mitigation in Cities of the Global South: The Case of Kumasi, Ghana. *Procedia Eng.* **2017**, *198*, 69–83. [CrossRef]
93. Jiang, W.; Deng, Y.; Tang, Z.; Lei, X.; Chen, Z. Modelling the Potential Impacts of Urban Ecosystem Changes on Carbon Storage under Different Scenarios by Linking the CLUE-S and the InVEST Models. *Ecol. Modell.* **2017**, *345*, 30–40. [CrossRef]
94. Sharma, R.; Pradhan, L.; Kumari, M.; Bhattacharya, P. Assessing Urban Heat Islands and Thermal Comfort in Noida City Using Geospatial Technology. *Urban Clim.* **2021**, *35*, 100751. [CrossRef]