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ORIGINAL ARTICLE

Evaluating Spatiotemporal Changes and Predicting Land-Use Dynamics Using an Artificial Neural Network in Worcester City, Massachusetts

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Abstract

The land use and land cover (LULC) change has a remarkable impact on the urban ecosystems due to its effect on the environmental processes, natural resources, and urban sustainability. The aim of this study was to conduct the spatiotemporal analysis of LULC in Worcester City, Massachusetts, and to identify the dynamics of forest cover and justify its causes in the given time range of 2003–2023. LULC classification and forest change detection were done with high-resolution datasets provided by the National Land Cover Database (NLCD). The MLP-ANN outperformed logistic regression and achieved higher in overall accuracy percentages and location Kappa values. Furthermore, a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) model embedded in the MOLUSCE plug-in of QGIS was used in order to forecast future LULC scenarios in 2033, 2043, and 2053. The findings showed that the built-up areas moved up from 82.1% to 83.2%, and the forest cover reduced from 12.4% to 11.9% over the period studied. Water bodies were relatively stable, wetlands were slightly raised, whereas the grasslands and barren lands recorded slight reductions. Forest change detection showed a total of 0.81% loss of forest, 0.03% gain of forest, and 99.10% change in forest that remained the same. The model validation was high (Kappa = 0.96), which proved that it can be used in the future to simulate it. The future LULC projections showed further urbanization and slow forest cover loss due to urbanization, control of pests, control of invasive species, and variability in climatic conditions. These results emphasize the necessity of implementing constant LULC monitoring during urban planning and policy regimes to make sure that the development is in balance with the minimum ecological impact.

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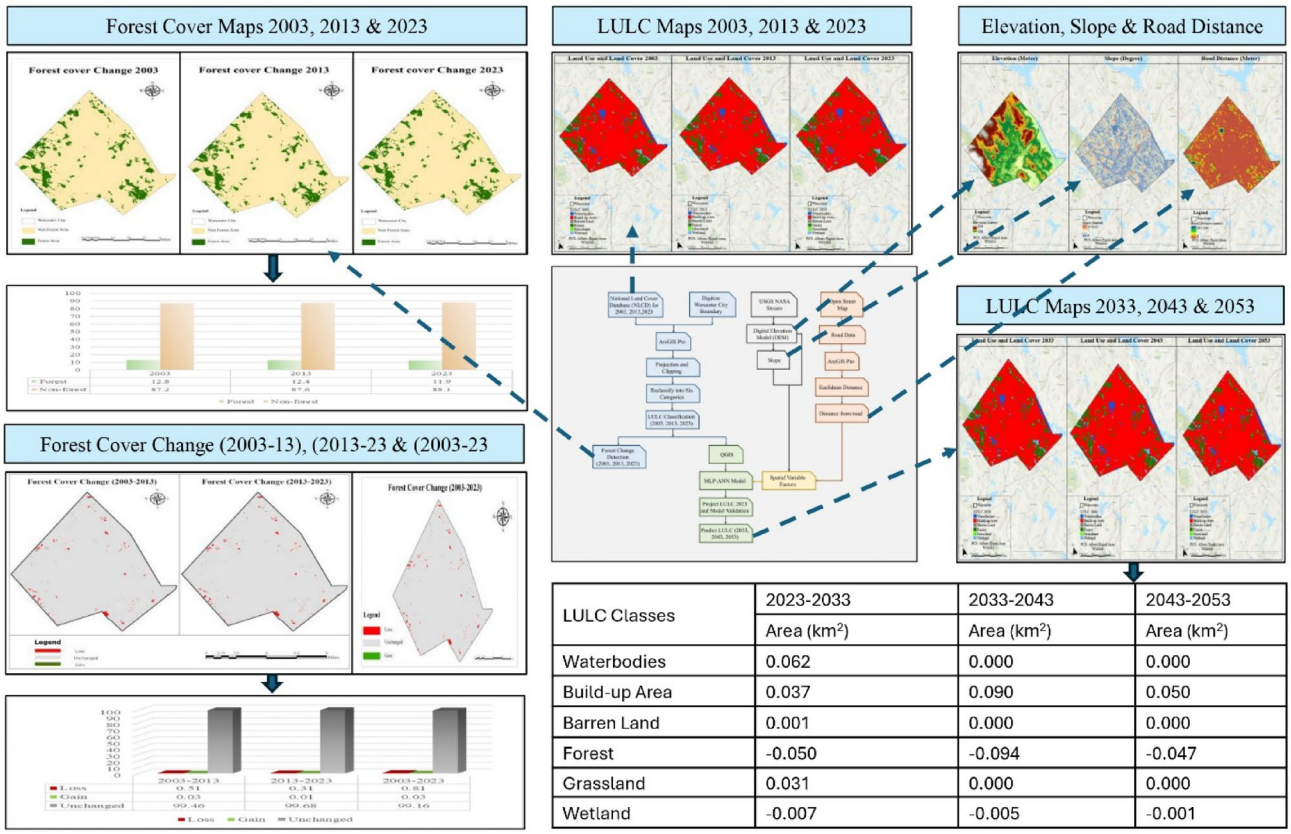
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Graphical abstract



LULC Classes	2023-2033	2033-2043	2043-2053
	Area (km^2)	Area (km^2)	Area (km^2)
Waterbodies	0.062	0.000	0.000
Build-up Area	0.037	0.090	0.050
Barren Land	0.001	0.000	0.000
Forest	-0.050	-0.094	-0.047
Grassland	0.031	0.000	0.000
Wetland	-0.007	-0.005	-0.001

The graphical abstract summarizes the study by visualizing the NLCD-based land cover data for Worcester City, Massachusetts, highlighting the high-resolution datasets used for analyzing LULC changes from 2003 to 2023. It illustrates the spatiotemporal analytical workflow, including LULC classification and forest change detection, used to quantify landscape transitions. The application of the MLP-ANN model within the MOLUSCE plug-in is depicted to show how future LULC scenarios for 2033, 2043, and 2053 were simulated. Key results are presented through comparative maps and statistics showing increased built-up areas, declining forest cover, and strong model accuracy (Kappa = 0.96). The final component visually conveys that continued urban expansion and gradual forest loss are expected, emphasizing the importance of ongoing LULC monitoring and sustainable planning to minimize ecological impacts.

Highlights

- National Land Cover Database (NLCD) datasets were used to analyze spatiotemporal LULC classification and forest change from 2003 to 2023 in Worcester City, Massachusetts.
- A Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) model within the MOLUSCE plug-in of QGIS was applied to simulate future LULC scenarios for 2033, 2043, and 2053.
- Built-up areas increased from 82.1% to 83.2%, while forest cover declined from 12.4% to 11.9%; forest change detection revealed 0.81% loss, 0.03% gain, and 99.10% unchanged forest.
- The MLP-ANN outperformed logistic regression and validation showed overall higher performance.
- Projected LULC patterns using ANN indicate continued urban expansion and gradual forest loss, underscoring the need for sustained LULC monitoring to support environmentally balanced urban planning.

Keywords LULC · Forest cover change · Multilayer perceptron · QGIS · MOLUSCE · Machine learning · Artificial neural network · MLP-ANN · Spatiotemporal · Prediction · Worcester

1 Introduction

Land Use and Land Cover (LULC) change is one of the most influential factors in modifying the environment, ecology,

and climate. LULC dynamics are influenced by numerous factors such as biophysical, socioeconomic, and technological factors explaining significant changes in land resources. Biophysical factors like changing climate, fluctuations in temperature and rainfall patterns, as well as natural events like landslides and soil erosion, affect the ecosystems (Lahai et al. 2022; Pokhrel and Kamar 2023). Population density, urbanization, and economic activities like mixed farming through agriculture, mining, and construction, infrastructure development are some of the main socioeconomic drivers of LULC change (Alemneh & Molla 2024; Iortyom et al. 2022). Technological factors like the adoption of new methods of farming practices, remote sensing, and geospatial data analysis tools assist in the observation of LULC changes yet provide agricultural expansion through forest clearance (Wang et al. 2023).

Observing LULC changes reveals how human activities impact land and offers information on developing effective and environmentally friendly strategies, especially in vulnerable areas (Raj et al. 2024; Yang et al. 2024). Alteration of land use affects species distribution and the services they provide for sustaining biological diversity (Aftab et al. 2024). Several studies show that biodiversity and the overall health of the forests are reduced by human interference, with an emphasis on the areas close to urban complexity (Guilbert et al. 2022). Many of these disturbances, such as fragmentation, pollution, and competition with invasive species, affect the viability of urban forests (Guilbert et al. 2022; Zhao et al. 2015). With urbanization, there is pressure on land usage for residential and infrastructural development; thus, housing encroaches on the forested areas (Lefulebe et al. 2022).

Significant LULC transformation occurred across the USA as well as in Worcester City, Massachusetts, due to urban development, application of environmental management, and pest control intervention. Between 1956 and 1975, city development was extensive, and subsequent flooding greatly increased, questioning the idea that inadequate drainage systems were the main cause (Visser 2014). Another major concern is loss of tree canopy cover; for instance, Worcester County lost 2% of it between 2008 and 2010. This loss was mostly attributed to low-density residential expansion (47%), followed by control efforts for invasive species such as the Asian long-horned beetle (25%), timber yield, and damages due to ice storms (Freilicher 2011; Hostetler et al. 2013). Clearing trees to control the growth of undesirable plant species also led to the rise in land surface temperature, thus increasing the intensity of urban heat islands (Elmes et al. 2017; Rogan et al. 2013a, b).

Zoning ordinances of South Worcester were adopted in 1963, and the construction of Route 290 changed land use from residential to non-residential use, which lowered environmental quality and desirability of living in the area (Conaty 1987). The post-war redevelopment approach in the city's historic core shifted from a large-scale urban renewal approach to a conservation-based approach, which illustrated an evolving consciousness to better control growth yet preserve the past (Vilagrasa and Larkham 1995). In Massachusetts, aboveground biomass gains have been reduced due to the conversion of forest areas to developed purposes. These dynamics, however, are being complicated due to climate change, as growth in tree cover is, at the same time, potentially reversed by continued growth in urban area extent and forest conversion (Duveneck and Thompson 2019).

Regardless of these challenges, to restore ecological balance and mitigate urban heat island effects, replanting initiatives are seen in the Worcester community. The adaptation to climate change and the mitigation of tree canopy loss, urbanization, and pest control are still central to the sustainability of Worcester. The environment and urban planning activities in the city require balancing between development and conservation, and improving the resilience of forests. Consequently, the study aims to determine the spatiotemporal dynamics of LULC in Worcester City between 2003 and 2023, and determine the change of forest cover and the factors that drive such change. Moreover, the research aims to predict and evaluate LULC changes in the years 2033, 2043, and 2053, using the Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) model. Such an integrated approach will provide detailed information about spatial and temporal changes in LULC and the forest cover of the city. Besides, the study seeks to identify the key drivers behind overall changes in land use patterns and forests from secondary literature and align them with the interpretation of results. The findings of the research will assist the urban planner and resource management authorities in targeted policy formulation for sustainable planning and urban development.

2 Materials and methods

2.1 Study Area

Worcester city in Massachusetts is a region that is shaped by its unique history, geographical features, and ecology. African Americans migrated here during the time of the Civil War (Greenwood 2016). Environmentally, the city has experienced numerous problems, evidenced by non-native plant species occupying between 21% and 36% of its landscape and being invasive to the natural ecosystem (Bertin and Parise 2014). Other invasive pests have also posed a threat to the indigenous vegetation, including maples through invasion by pests such as the Asian long-horned beetle

(Shatz et al. 2013). Urban development and pest management activities during the years 2008–2010 quantitatively reduced tree canopy cover by 2% (Hostetler et al. 2013). The geographical attributes can be judged by the fact that it has slopes, glacial water fields, swamps, and a variety of vegetation, mainly Eastern Deciduous Forest (Weatherbee and Crow 1990). However, the increase in factors such as urbanization and later colonization by non-native species persists to pose a threat to increasing ecological insensibility, hence the call for sustainable conservation measures (Hostetler et al. 2013). To give attention to local sustainable measures, localized LULU change assessment plays a significant role as it gives specific direction on how lands are being used in a city. Additionally, forest change detection provides meaningful information to take necessary steps for the sustainable conservation of natural resources. Further, limited research has been conducted on localized research related to Worcester city. Thus, Worcester city has been chosen for the current research (Fig. 1).

2.2 Data and Criteria

The datasets utilized in this study comprise the Digital Elevation Model (DEM), slope data, a road network, and three Land Use/Land Cover (LULC) maps from the years 2003, 2013, and 2023. The LULC datasets were taken from the Multi-Resolution Land Characteristics (MRLC) Consortium (https://www.mrlc.gov/data) with a spatial resolution of 30 m. We got elevation and slope data from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/) while keeping the same level of detail. The road network data were retrieved from the OpenStreetMap (OSM) database (https://download.geofabrik.de/north-america/us.html) in polyline shapefile format.

The elevation and slope raster were used to represent terrain variability, while the road network was transformed into a Euclidean distance raster to capture accessibility gradients that potentially drive urban growth and land use modifications. To ensure spatial consistency, all raster datasets were resampled to a uniform 30-meter resolution and spatially aligned to a general extent. The detailed descriptions and data sources are summarized in Table 1.

In this study, DEM, slope, and distance from roads (Fig. 2) were utilized as primary driving factors in conjunction with the historical LULC layers. These variables were selected due to their established significance in influencing land use dynamics, particularly in processes such as urban expansion, deforestation, and wetland transformation. In addition, we excluded temperature and population variables due to the poor resolution of climate grids for local analysis (and resampling introduces uncertainty) and the reliance of many population datasets on land cover or nighttime lights, which may result in circularity with the built-up class.

2.3 LULC and Forest Classification of Worcester City

Land use/land cover (LULC) classification was performed to aggregate detailed land cover information into analytically meaningful categories for change detection. Based on NLCD class definitions and their relevance to urban

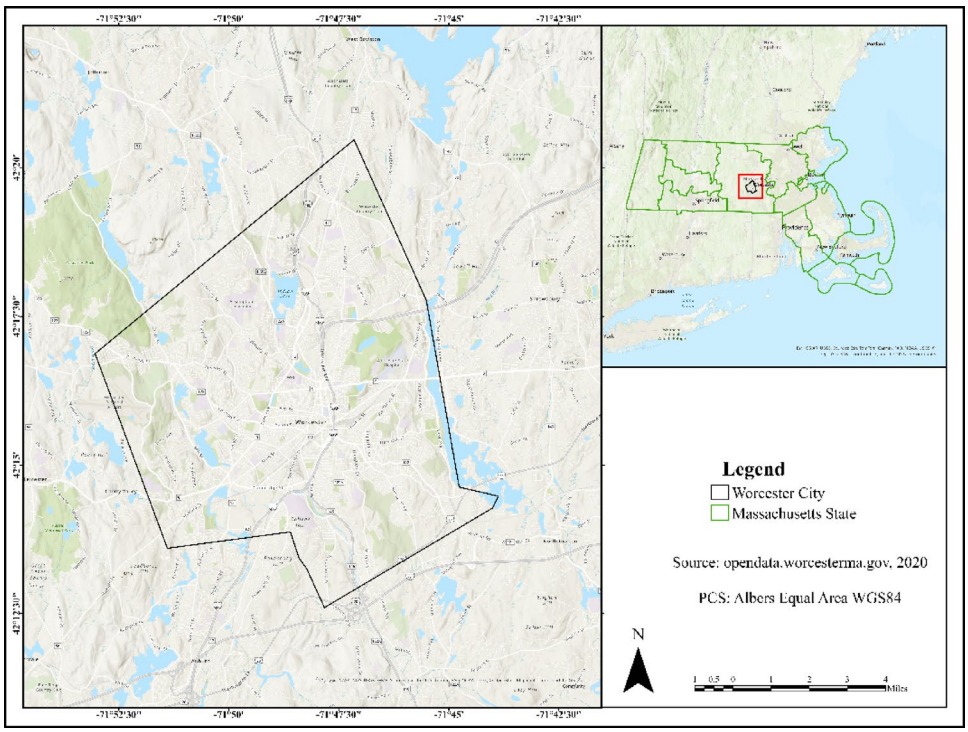


Fig. 1 Map of the study area

Table 1 Data Sources

Dataset	Type	Geometry/ Resolution	Time	Source	Format
Elevation	raster	30 m	-	U.S. Geological Survey (USGS)	GeoTif
Slope	raster	30 m	-	U.S. Geological Survey (USGS)	GeoTif
Road Network	vector	polyline	-	Geofabrik GmbH	Shapefile (.shp)
LULC	raster	30 m	2003, 2013, and 2023	(Multi-Resolution Land Characteristics (MRLC) Consortium, n.d.)	GeoTif
Worcester Boundary	vector	polygon	-	(City of Worcester, MA, n.d.)	Shapefile (.shp)

and environmental processes (USGS 2025), land cover was reclassified into six categories: water bodies (Class 11), built-up areas (Classes 21–24), forest (Classes 41–43), grassland/shrubs (Classes 52, 71, 81), wetlands (Classes 90 and 95), and barren land (Class 31). This reclassification enhanced the interpretation of dominant land use transitions by preserving the ecological and urban significance of each class. Class-wise area statistics were calculated and expressed as percentages of the total study area to enable temporal comparison of land use changes across the three reference years.

Furthermore, to examine forest dynamics, a change detection analysis was conducted focusing on NLCD forest classes (41–43). Forest areas were isolated from other land use categories to enable consistent tracking of forest presence and absence across the three reference years (2003, 2013, and 2023). Forest cover changes were quantified for the intervals 2003–2013, 2013–2023, and 2003–2023, allowing identification of forest gain, forest loss, and stable forest areas. Percentage changes were calculated for each interval to assess the magnitude and rate of forest cover change over time, providing a temporal perspective on forest dynamics.

2.4 Forest Change Detection

To understand forest dynamics, a detailed change detection analysis was performed:

Forest classes within NLCD, consisting of 41, 42, and 43, were assigned a value of 1, and all other classes of land use were assigned a value of 0. Forest data for the years

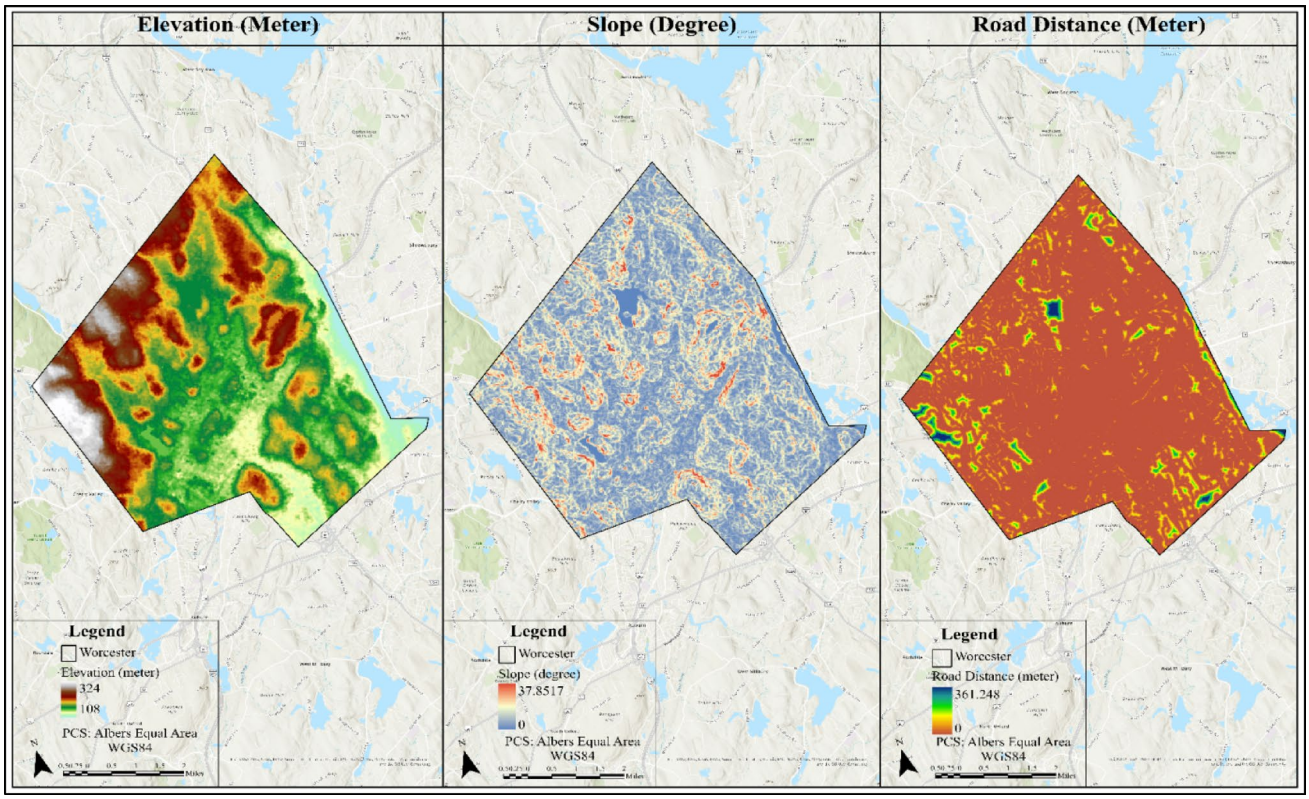


Fig. 2 Spatial variables used in the study

2003, 2013, and 2023 were reclassified to the vector format to improve the dataset and dissolve them by classification value. The "Change Detection" tool was applied to quantify forest changes across three-time intervals: 2003–2013, 2013–2023, and 2003–2023. Finally, this analysis captured the changes in the extent of forest, categories of forest extent change, and the no-change areas, and therefore offered a temporal view of the forest. Percentage changes were also computed on the forest cover changes for each interval, providing an understanding of the rate of forest gain/loss at the different intervals.

2.5 Prediction and Model Validation

2.5.1 Method

We utilized the CA-ANN approach integrated within the MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS to model transition potentials and simulate future land use and land cover (LULC) changes. The CA-ANN technique is favored in recent scholarly literature for its superior ability to model non-linear relationships and spatial dependencies compared to conventional linear regression methods. Area change analyses and transition probability matrices were produced using the 1990 and 2002 LULC datasets (Das et al. 2025). Cellular automata (CA)-based models are spatially explicit models (SEM) that work on a simple premise that the future state of a land cover type is dependent on the past local interactions between the different land covers (Gharaibeh et al. 2020; Mehra and Swain 2024). The accuracy of the model was dependent upon the temporal scale of maps, neighboring cells, and transition rules (Santé et al. 2010; Sarkar 2000). Artificial neural networks (ANN) can identify and analyze the complex inter-relationship between causative factors and complex patterns (Aburas et al. 2016; Mehra and Swain 2024). The architecture of an ANN simulates and behaves in a similar pattern to the human brain and nervous system (Wu et al. 2022). ANN can handle incomplete data, does not assume the distribution of input data, and can detect potential interdependencies between driving factors (Mehra and Swain 2024; Tayyebi and Pijanowski 2014). Researchers have adeptly employed CA-ANN models to address spatial-dynamic complexities and driving factors, enhancing the robustness and realism of modeling for accurate prediction and estimation of land cover changes.

2.5.2 Model Evaluation

LULC maps from 2003 to 2013 were used as baseline inputs to calibrate transition probabilities. Elevation, slope, and distance from roads were incorporated as spatial driving factors due to their established influence on land development and landscape transformation. Using the calibrated transition rules, future LULC scenarios were projected for 2033, 2043, and 2053, assuming that historical transition patterns and driving processes remain stable over time.

The relationships among spatial driving variables were evaluated using Pearson's correlation coefficient to assess the degree of association and potential multicollinearity among predictors prior to model calibration. (Dormann et al. 2013; Kamwi et al. 2018; Abdullah et al. 2019) Land use distributions and LULC changes between the base year (2003) and the final calibration year (2013) were then quantified to establish observed transition patterns. A transition matrix was generated to estimate the proportion of pixels shifting between land cover categories during the calibration period, providing the basis for modeling transition dynamics. Changes in the spatial extent of each LULC class were calculated in square kilometers to quantify gains and losses across the study area.

After generating the transition matrix, transition potential maps were generated using an MLP-ANN. CA-ANN is particularly valued for simulating complex land transitions in heterogeneous landscapes (Li and Li 2015). Prior studies, in China (Muhammad et al. 2022) and in Kazakhstan (Alipbeki et al. 2024), have validated its effectiveness in LULC modeling. The ANN was trained on 1000 sample points with a learning rate of 0.01, momentum of 0.05, 10 hidden layers, and 1000 training iterations. Sample points vary across the region (Farhan et al. 2024; Tariq and Shu 2020; Zhang et al. 2025). Following the generation of transition potential maps, a CA model was implemented to allocate changes based on the transition probabilities spatially(Mohamed and Worku 2020).

2.5.3 Transition Potential Modelling

Several transition potential modeling approaches are available, but among the available transition potential modeling approaches, the Multi-Layer Perception Artificial Neural Network (MLP-ANN) was selected due to its ability to capture non-linear relationships between historical LULC transitions and spatial driving factors. The calibrated model was used to simulate the 2023 LULC map, and prediction accuracy was evaluated by comparing the simulated output with the observed 2023 LULC map using the Kappa coefficient. To benchmark performance, Logistic Regression (LR) was also implemented as a baseline model for comparison and compared through overall Kappa. A statistical measure frequently employed in categorizing land use and land cover is the Kappa coefficient, which is especially useful for accuracy assessment (Gunathilaka and Fernando 2022; Waghela et al. 2022).

2.5.4 Validation

Model validation was performed using historical data from 2010 to 2020 to assess prediction accuracy (Ullah et al. 2024). The validated model was then used to project urban growth patterns to 2030, incorporating current growth trends and spatial constraints. The entire methodological framework was designed to ensure reproducibility and reliability in analyzing historical LULC changes and projecting future urban growth scenarios for the study area (Hamad et al. 2018; Zhang et al. 2025). The Kappa coefficient served as the evaluation method to determine the accuracy of LULC prediction results. One common statistical method for assessing the level of agreement between classification and reference map data is the Kappa coefficient. In the case of the classification of the 2023 predicted LULC map relative to the reference map, the Kappa evaluation calculated an overall Kappa value. The Kappa coefficient is calculated using the following equation (Ullah et al. 2019; Alawamy et al. 2020):

$$Kappa = \frac{P_0 - P_e}{1 - P_e} \tag{1}$$

where P_0 is the percentage of observed (actual) agreement, and P_e is the percentage of agreement that was expected by chance. These values are calculated as:

$$P_0 = \sum_{i=1}^{c} P_{ij} \tag{2}$$

$$P_e = \sum_{i=1}^{c} p_i T p T_j \tag{3}$$

Here, P_{ij} *refers* to the value in the i^{th} row and j^{th} column of the contingency matrix, $p_i T$ *refers* to the sum of all cells in the i^{th} row, pT_j refers to the sum of all cells in the *j*th column, and *c* denotes the total number of raster categories.

The contingency matrix, used in this study, represents the frequency distribution of classified and reference categories, illustrating how the *i*th and *j*th cells correspond to each other. Each cell's connection was measured to determine the degree of agreement between predicted and actual LULC classes. Multiple simulation experiments were conducted to create the LULC prediction map for 2023 using different combinations of spatial explanatory variables. Among these, three key spatial variables were ultimately selected for optimal model performance and accuracy (Fig. 3).

3 Results and Discussion

3.1 LULC change of Worcester city

The analysis of the LULC changes of Worcester city for the years 2003, 2013, and 2023 indicates the progressive urbanization and utilization of the natural resources. The percentage of water bodies has shown a slight decrease over the two decades from 2.7% in 2003 to 2.6% in 2023. This is really a very small variation, implying that the resources of water in the city are not much influenced by different land uses.

The most significant trend here is the growth in built-up areas that have risen from 82.1% in the year 2003 to 83.2% in the year 2023. This rise indicates the expansion of urban area, which may have been fueled by high population densities, sizeable investments in infrastructure, and increasing need for housing and other premises. Conversely, the forest cover shrinks from 12.8% in 2003 to 11.9% in 2023, suggesting increased encroachment by urban development and change of land use priorities(Fig 4, 5).

LULC in Worcester city.

A second type of vegetation, grasslands and shrublands have declined significantly from 0.1% in 2003 to 0.06% in 2023. This loss might be due to urbanization and the transformation of the natural habitat into built environments. Wetlands, however, have a small rise from 2.1% in 2003 to 2.21% in 2023, which gives an indication that there are probably some conservation measures and or adaptive land use that might help in the provision of wetland conservation and development. The dramatic shift is evident in the barren land that has reduced to a bare 0.03% in 2023 from 0.2% in 2003. This drastic decrease presupposes that the land that has previously remained unoccupied has most probably been reclaimed for construction or for more efficient use compatible with the trends corresponding to the concept of urbanization and reclaiming of lands.

Overall, the changes in Worcester's land use patterns revealed over the course of the past two decades reveal a consistent expansion of built-up areas alongside a constant reduction in natural habitats such as forests and grasslands. Though the stability of the water bodies and a slight increase in the size of wetlands show that the city has at least continued to preserve other natural resources for development.

3.2 Class-wise Accuracy Assessment

Using Google Earth Pro's high-resolution visual interpretation as a guide, we independently evaluated the thematic accuracy of the NLCD-based LULC maps. The Multi-Resolution Land Characteristics (MRLC) Consortium, coordinated by the U.S. Geological Survey, developed the nationally uniform 30-meter land cover product known as

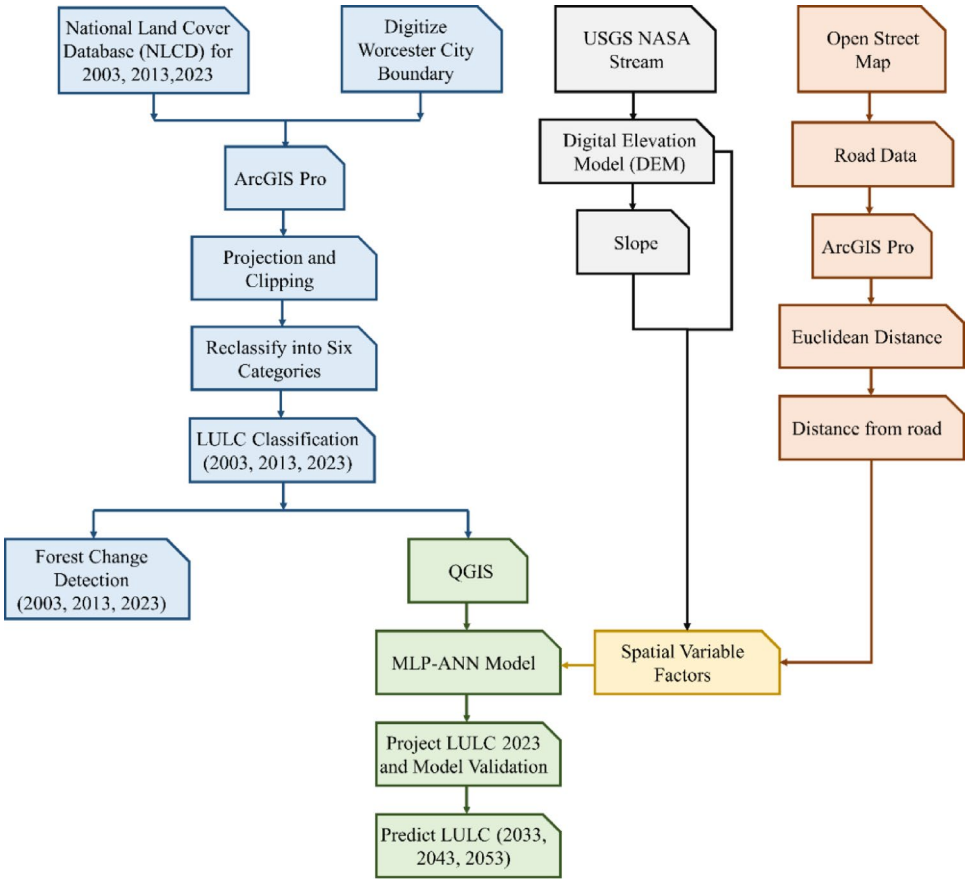
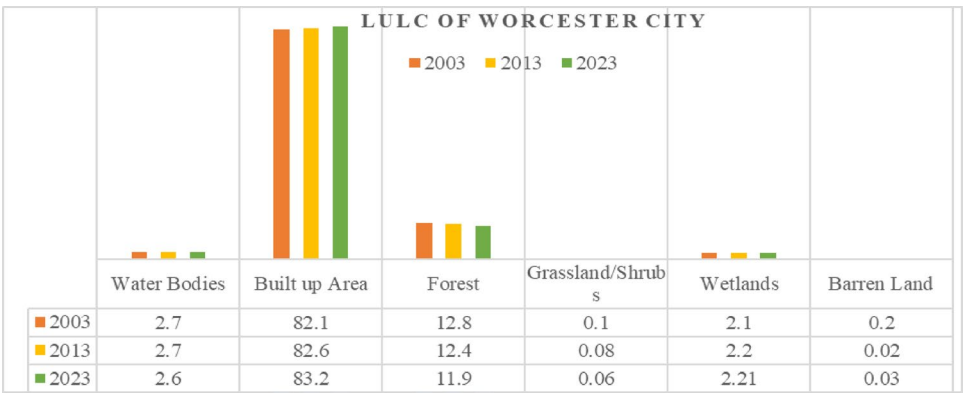


Fig. 3 Methodological flowchart



	Water Bodies	Built up Area	Forest	Grassland/Shrubs	Wetlands	Barren Land
2003	2.7	82.1	12.8	0.1	2.1	0.2
2013	2.7	82.6	12.4	0.08	2.2	0.02
2023	2.6	83.2	11.9	0.06	2.21	0.03

Fig. 4 Temporal variation of

NLCD, even though it is considered a secondary dataset. We employed stratified random sampling to generate validation samples. Confusion matrices, along with class-wise User's Accuracy (UA) and Producer's Accuracy (PA), were generated by comparing the map labels at each sample location with reference interpretations in ArcGIS Pro.

Table 2 illustrates how accurate the NLCD-derived LULC maps were for 2003, 2013, and 2023, using $N = 134–135$ reference samples. Overall, the agreement is moderate to good, with OA = 0.806 (Kappa = 0.696) in 2003, OA = 0.873 (Kappa = 0.796) in 2013, and OA = 0.830 (0.730) in 2023. An additional examination in 2023 depicted OA = 0.859 and Kappa = 0.776. Over these years, waterbodies and built-up areas have been the most reliable classes (waterbodies: UA ≈ 0.90–1.00; PA = 0.90–1.00; built-up: UA ≈ 0.86–0.89; PA ≈ 0.97–1.00). This result quantifies that changes in the categories can be interpreted with confidence. In contrast, uncertainty is higher for minority and heterogeneous classes: forest showcases noticeably lower Pa in 2023 (0.48–0.63) despite high UA (0.92–1.00), while grassland exhibits persistently low PA (0.41–0.50) and wetland drops rapidly in 2023 (UA = 0.20–0.50; PA = 0.50–0.71), denoting greater omission or commission error risk for these classes.

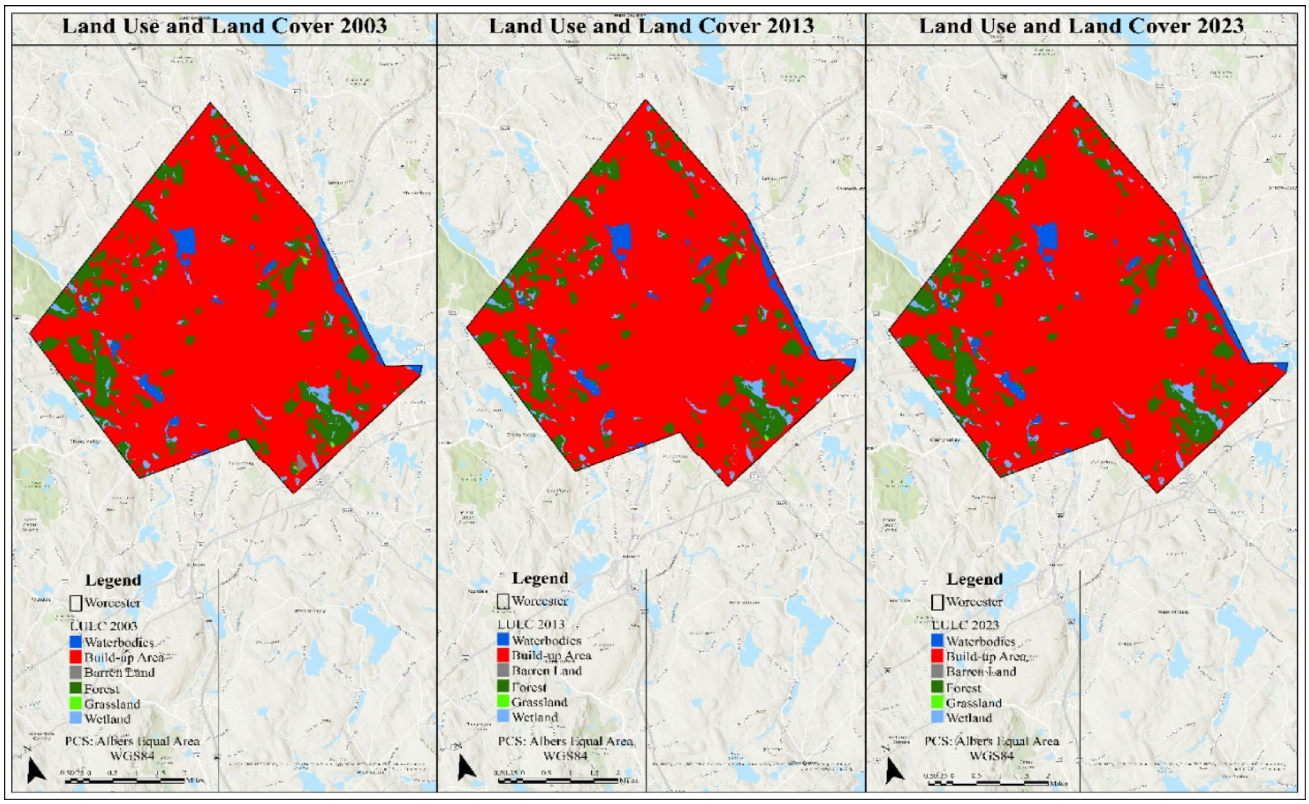


Fig. 5 LULC maps of Worcester city for 2003, 2013 and 2023

Table 2 Confusion Matrix

Matrix	2003	2013	2023
Total samples (N)	134	134	135
Overall Accuracy (OA)	0.805970	0.873134	0.859259
Kappa	0.696039	0.796462	0.775689
UA Waterbodies	0.900000	0.900000	0.9
PA Waterbodies	0.900000	1.000000	0.9
UA Buildup	0.864198	0.890244	0.89156611
PA Buildup	0.972222	0.973333	1
UA Barren	0.700000	0.700000	1
PA Barren	0.538462	1.000000	0.833333
UA Forest	0.692308	0.833333	1
PA Forest	0.642857	0.833333	0.631579
UA Grassland	0.700000	0.900000	0.6
PA Grassland	0.500000	0.409091	0.461538
UA Wetland	0.600000	0.900000	0.5
PA Wetland	0.545455	1.000000	0.714286

Because Producer Accuracy (PA) is the opposite of omission error, and User's Accuracy (UA) is the opposite of commission error, lower UA or PA refers to map areas and from-to transitions for wetland or grassland are more likely to be affected by classification uncertainty. Furthermore, post-classification alteration detection superimposes two independently classified maps, allowing errors from time steps to showcase us apparent changes. Consequently, minor net changes and transitions among lower-accuracy classes should be interpreted with greater caution than those including built-up areas and water. As an additional limitation, our reference interpretation utilized Google Earth Pro single-date imagery, which may not align with the NLCD specific-year Landsat composite strategy, such as leaf-on/ leaf-off and multi-image compositing. Furthermore, wetlands can manifest crucial variability due to seasonal and inter-annual inundation dynamics. This temporal discrepancy may exaggerate apparent wetland commission or omission and introduce uncertainty to wetland-related transitions, particularly between 2013 and 2023.

3.3 Forest cover change in Worcester city

Worcester city has experienced a slow reduction in forest cover over the 20 years between the year 2003 and 2023. Total forest area constituted to 12.8% of the city's total land area and the (Fig 6, 8).

The non-forest region constituted to 87.2% of the total land area of the city in the year 2003. Whereas in the year 2013, forest cover had come down to 12.4%, on the other hand, non-forest area has risen to 87.6%. This trend continued into the year 2023, in which forest cover reduced to 11.9%, and non-forest area rose to 88.1%.

These declining trends in forests express the continuous conversion of the area for urban development and the

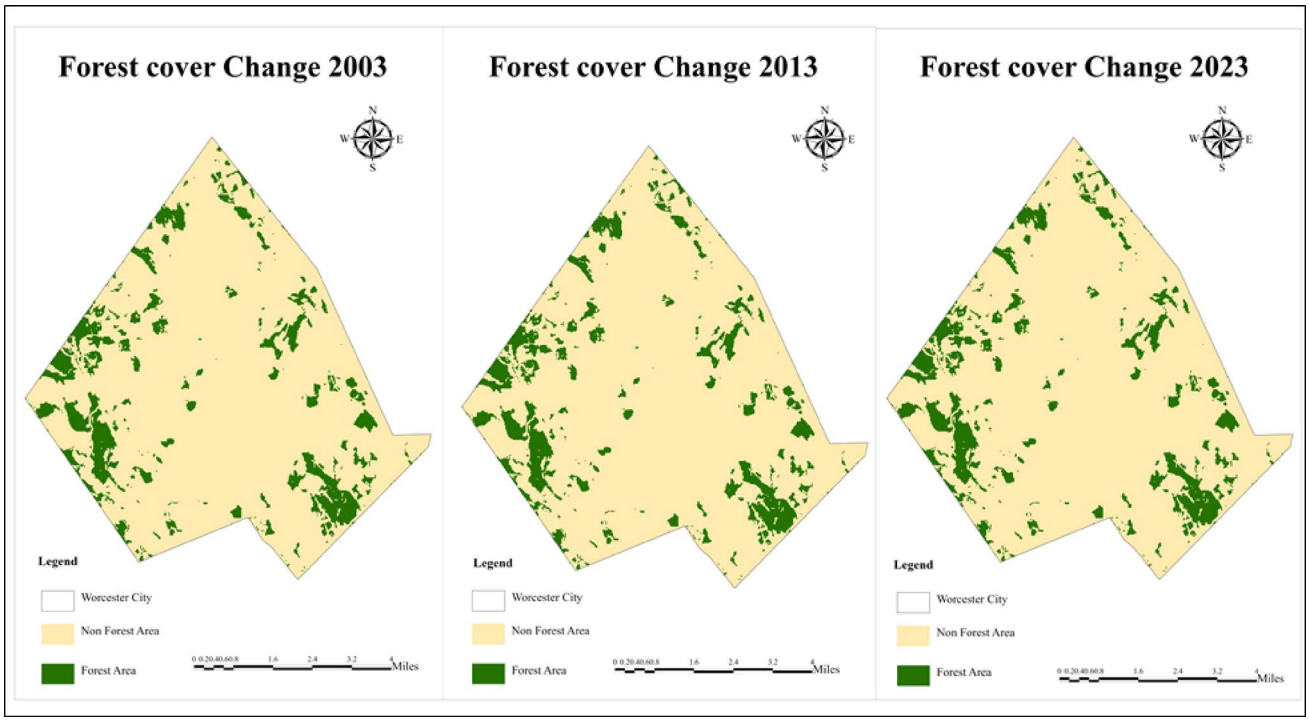


Fig. 6 Forest cover change maps of Worcester city for 2003, 2013, and 2023

modification of the land use system for infrastructures, housing, and others. Breaking it down further, forest loss during 2003 and 2013 was 0.51% while forest gain was only 0.03%, and the rest 99.46% remained unchanged. Between 2013 and 2023, the decline proved somewhat less pronounced, forest cover decreasing 0.31%, gains increasing 0.01%, and 99.68% of the forested area remaining unchanged.

Thus, the average forest cover loss across the whole 20-year period was only 0.81%, coupled with gains of 0.03% of forest and 99.16% of no change. The above figures imply that Worcester has been observed to have a relatively small diminution of the forest cover. Despite urban development and other changes in land use in Worcester city, most of the forest areas have been in a steady state that harms the entire ecosystem (Hostetler et al. 2013 a; Haddad et al. 2015) as Worcester city provides the whole ecosystem services with air quality, stormwater, carbon storage, and sequestration (WCC 2024).

3.4 Influencing Drivers Behind the Changes of Lulc And Forest Cover

According to data analysis and secondary literature review, factors including increasing urban areas (Rogan et al. 2013a, b; Thorn et al. 2016), pest control activities (Dodds and Orwig 2011; Hostetler et al. 2013 b; Varuzzo and Harvey 2017), climate shifting (Duveneck and Thompson 2019), and conservation practices (Nolte et al. 2019) caused Worcester City's LULC and forest cover to change from 2003 to 2023.

In terms of different parts of Worcester city (Fig. 9), between 2003 and 2023, the northern Worcester City neighborhoods of Morning Dale and Great Brook Valley showed moderate forest disappearance. Forest loss appeared through fragmented open spaces instead of expansive, spanned clearings in this region. Forest gain occurred across the area, but it remained scarce and discontinuous when compared to the total region of forest loss. Different signs of forest degradation emerged along with weak natural regeneration patterns in this region (Fig 10).

A comprehensive forest clearance occurred across the southeastern area consisting of Grafton Hill and Broadmeadow Brook, together with East Millbury, throughout the research period. The central section, together with the southern perimeter of affected areas, showed the highest rate of forest loss, possibly because of developing urban construction activity and changes in land usage patterns. Forest regeneration occurred in scattered small areas, although these remained insufficient to counter the complete forest loss. Data shows an increasing demand for forested areas in this area.

The southwestern territorial area that contains Webster Square and Hadwen Park, together with Cherry Valley, displayed the largest amount of forest area disappearance. Extensive deforestation occurred in this region, where persistent dense clearings created massive clearing areas. The

large scale of deforestation in this area indicates a high level of environmental degradation that warrants immediate conservation action.

The main forces for change in LULC and forest cover have been urban expansion across the city, with urban areas rising from 82.1% to 83.2% in two decades. The growth of population and urbanization leads to an increase in demand for new houses, businesses, and roads. The growing demand for these things has forced development companies to convert forest and grasslands into built-up areas (Duveneck and Thompson 2019; Rogan et al. 2013a, b). The built-up part of Worcester County now takes up 83.2% of the land, pushing out forests (from 12.8% to 11.9%) and grasslands (from 0.1% to 0.06%), showing clear urban expansion into natural areas. Similar changes are observed in cities around the world, where towns grow fast but make little effort to keep nature intact (Lefulebe et al. 2022).

The control of invasive species - mainly focusing on the Asian long-horned beetle - has reduced Worcester County's tree canopy dramatically. During the 2008–2010 period, the forest canopy declined by one-fourth due to activities needed to control invasive species and pests, which harmed forests by killing their trees (Freilicher 2011; Hostetler et al. 2013). Harvesting timber and ice storms have played a part in shrinking Worcester County's Forest cover (Elmes et al. 2017).

Climate change relates directly and indirectly to forest cover change. Increased temperature and more unpredictable rainfall patterns negatively impact forest health and growth, dependent on higher frequency of storms means trees experience weather conditions are less predictable (Duveneck and Thompson 2019). Urban heat islands and loss of vegetation compound other issues that detract from forest health and increase susceptibility to certain insect attacks and diseases (Rogan et al. 2013a, b).

Table 3 Model Comparison

Metric	Logistic Regression	MLP-ANN	Best
% of Correctness	98.42532	99.04606	ANN
Kappa (overall)	0.94716	0.96822	ANN
Kappa (histogram)	0.98620	0.98034	LR
Kappa (location)	0.96041	0.98764	ANN

3.5 Model Comparison

The table shows how well logistic regression and MLP-ANN performed on four different tests. MLP-ANN has higher overall Kappa (0.96822 vs. 0.94716), and Kappa location (0.98764 vs. 0.9604. Logistic regression only beats Kappa (histogram) (0.98620 vs. 0.98034), which means that the class amounts are a little more in agreement.

Though logistic regression yielded marginally superior quantity agreement (Kappa histogram); nonetheless, MLP-ANN was selected due to its enhanced overall accuracy and spatial (location) agreement, signifying a more reliable forecast of the geographic distribution of LULC change. Moreover, MLP-ANN, consists of input layers, hidden layers, and an output layer, and is the widely used model in ANN because it is fast, accurate, and can infer and forecast outcomes derived from inputs that it has not encountered previously, exhibiting the capacity for extrapolation and prognostication (Atkinson and Tatnall 1997; Mehra and Swain 2024) (Table 3).

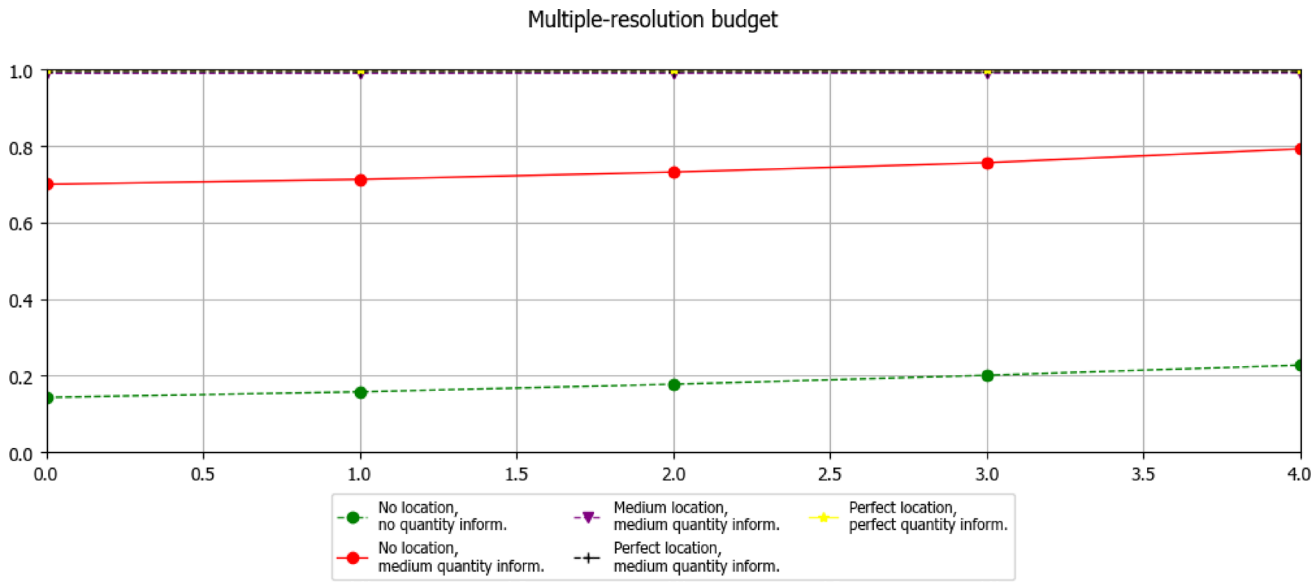


Fig. 11 Validation graph of actual LULC (2023) and simulated LULC (2023)

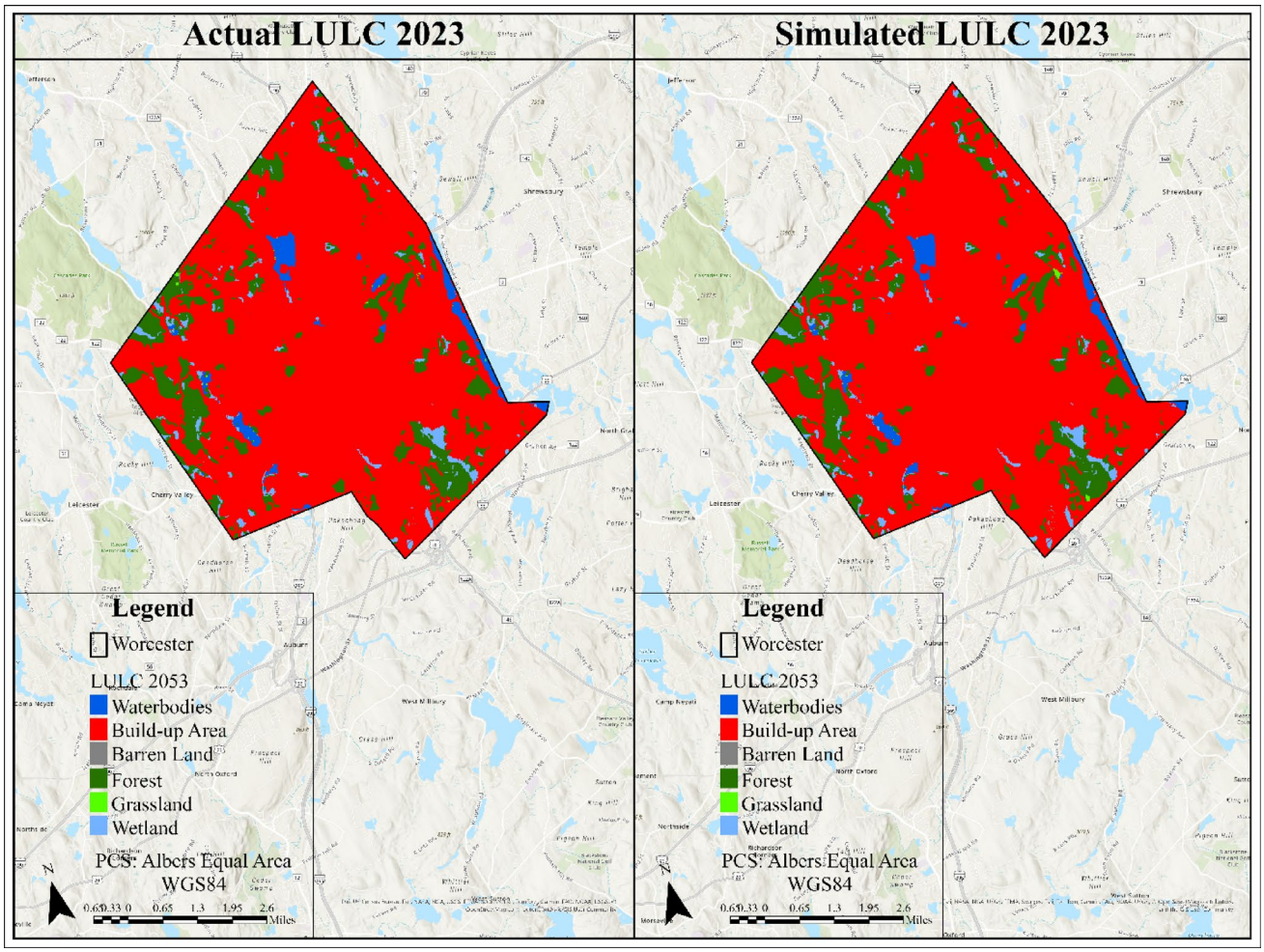


Fig. 12 Map of Actual LULC (2023) and simulated LULC (2023)

3.6 Predicted LULC Simulation

3.6.1 Model Validation of Predicted LULC

In this study, the LULC map was prepared in QGIS and was validated for the year 2023. The MOLUSCE plugin was used to compare the simulated and actual 2023 LULC data through kappa statistics. The validation process showed that the system achieved 98.82% correctness and $K_{overall}$ score of 0.96041 and K_{histo} value of 0.988 and K_{loc} score of 0.971. The future land use prediction using the model had acceptable accuracy rates as all the kappa values are above the 80% threshold (Amgoth et al. 2023; Baghel et al. 2024; Kamaraj and Rangarajan 2022). The model performance showed reliable predictions for 2033 and 2043 and 2053 land use change because the 2023 forecast results aligned with actual observed land change patterns. Figures 11 and 12 represent the validation graphs and maps of the observed and predicted LULC in 2023.

3.6.2 Future LULC Simulations for 2033, 2043, and 2053

The same method was used to create the future LULC maps of 2033, 2043, and 2053 as in the case of the 2023 prediction. These years are predicted to have the LULC distribution as indicated in Fig. 7. The findings represent minimal changes in forest, wetlands, and built-up areas. The work established those built-up areas continuously grew in 2033, 2043, and 2053, primarily because of the high rate of population growth, and they occupied 83.61 km^2 (83.21%), 83.70 km^2 (83.31%), and 83.75 km^2 (83.35%), respectively (Table 4). Conversely, forests and wetlands were still shrinking as they were turned into developed land. It was expected that the area of forests would decrease to 11.96 km^2 (11.90) in 2033, 11.86 km^2 (11.81) in 2043, and 11.82 km^2 (11.76) in 2053 because of an increase in the built-up area, which was projected by the model (Table 5). The LULC maps (Fig. 13) indicate clearly that the forest cover is declining due to human activities, whereas the urban areas are growing in terms of population. These changes were

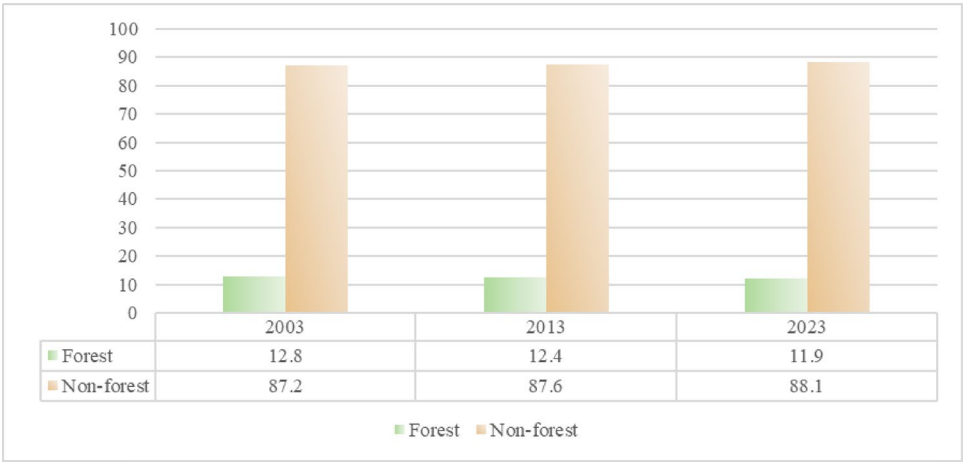


Fig. 7 Temporal distribution of forest cover in Worcester city

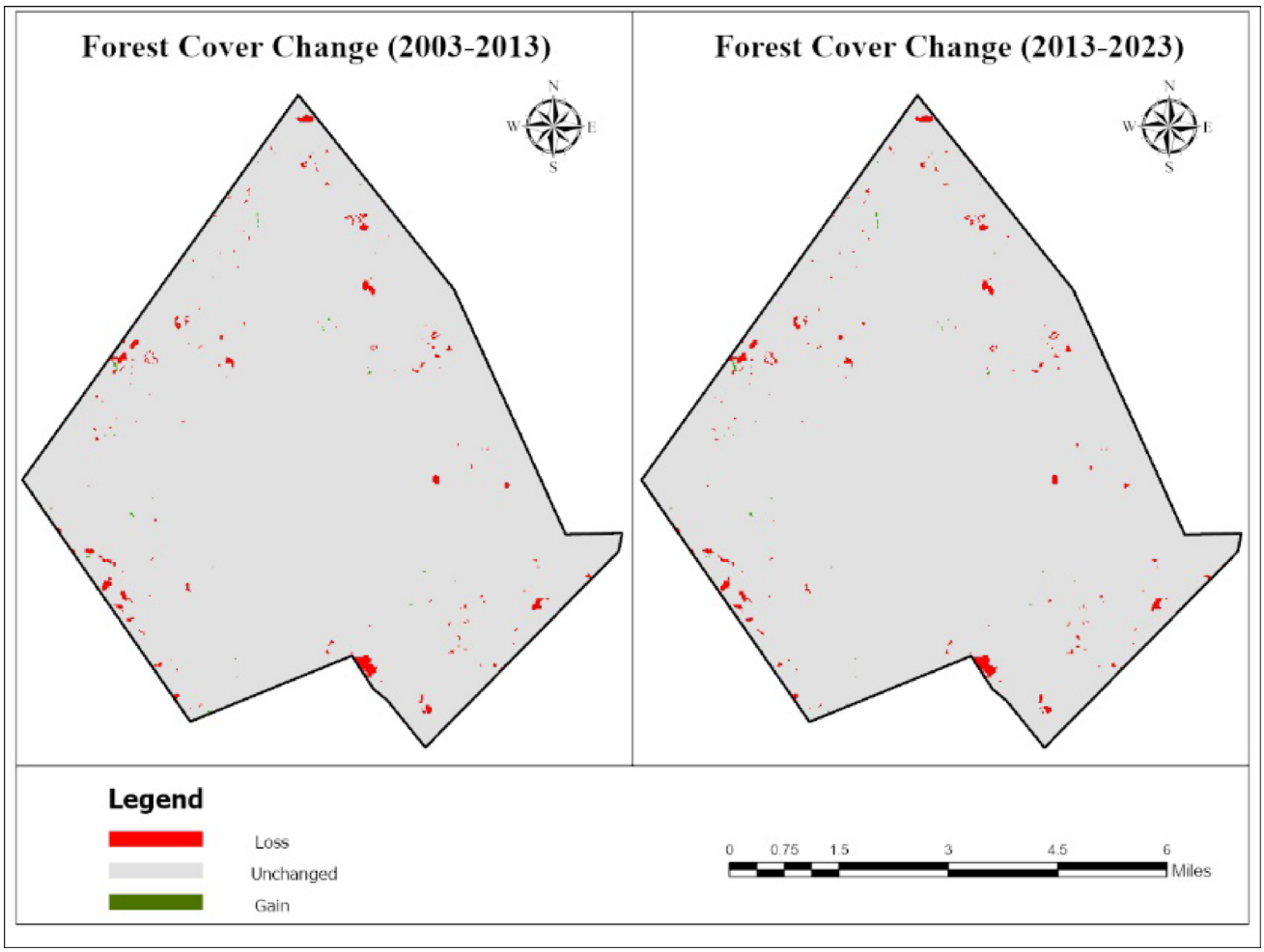


Fig. 8 Spatial changes of forest cover: Loss, gain & unchanged

also analyzed in terms of percentages of the total land area. The same examples have been stated in earlier literature, which proves the effectiveness of the CA-ANN model to predict future changes in LULC (Baghel et al. 2024; Mitra et al. 2023; Uddin et al. 2023).

3.6.3 Certainty Analysis

Figure 14 illustrates that high certainty (class 3) predominates the research region (92.29%), signifying robust trust in the ANN forecasts. Low (class 1) and medium (class 2)

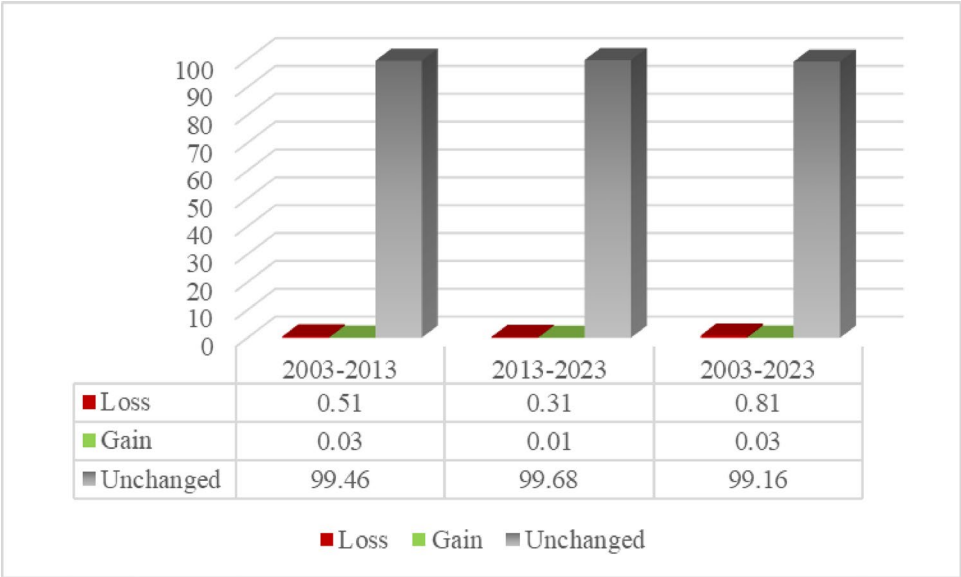


Fig. 9 Temporal changes in Forest cover: Loss, gain & unchanged

certainty comprise merely 3.33% and 1.60%, respectively, and predominantly manifest as dispersed patches among varied land-cover mosaics and class boundaries where transitions are more challenging to delineate. This study classified the ANN certainty output into three confidence levels: 1 for low, 2 for medium, and 3 for high. Regions of high certainty (class 3) encompassed the majority of the research area, indicating substantial confidence in the model. Regions of medium and low certainty (classes 2 and 1) were predominantly located in dispersed patches, primarily inside heterogeneous areas and land-cover boundaries where distinguishing between classes is more challenging.

3.7 Limitations and Future Direction

While the study provides valuable insights, it also exhibits some limitations. First of all, the study utilized the National Land Cover Dataset, which may limit the capture of land cover details due to its moderate resolution. Secondly, the selected timeframe for thirtyyear period may overlook short-term changes in the city. Thirdly, to identify the key drivers, the study solely relied on secondary literature and the interpretation of the analysis. So, there is a lack of field validation due to budget and logistical constraints. We therefore validated forest loss and urban expansion patterns using historical high-resolution reference imagery in Google Earth Pro. Historical very-high-resolution reference imagery is uneven across time, and Sentinel-2 is unavailable prior to 2015, which constrains validation for early years. Lastly, the applied MOLUSCE models forecast future LULC considering past trends, but these models not consider the government policy interventions, climate adaptation efforts, or unexpected environmental disturbances. We kept a small set of drivers for these reasons: to avoid overfitting and to make the model easier to use in other situations. Future research should use more advanced datasets, conducting field validation as well as an extended temporal scope. Additionally, the predicted model needs to incorporate socio-economic and climate data to test different possible scenarios and also understand the major drivers behind LULC changes and the relationship between the drivers. Moreover, our future LULC maps should be interpreted as conditional Business As Usual (BAU) simulations, not deterministic forecasts. The projections assume that transition tendencies estimated from the historical period remain approximately stationary over time and that the modeled relationships between drivers and transitions, as well as CA neighborhood effects, remain valid during the projection horizon; therefore, substantial policy changes, conservation enforcement shifts, or climate-related shocks could alter future trajectories.

3.8 Recommendation

A set of strategies can help Worcester City to manage its land use and forest cover challenges. Increased urban forestry programs and the creation of green spaces can help in taming the urban heat island, creating cleaner air while saving wildlife. The developers need to be able to follow sustainable urban development plans, protecting forests and natural areas alongside building new infrastructure. Using modern tools like remote sensing and mapping helps to track how land is used and how forests stay healthy. This assist in making better decisions possible at the right time. The community needs targeted strategies that promote adaptation to climate change challenges and safeguard fragile ecosystems while rewarding eco-friendly farm management methods. Local people need to join efforts in preserving nature, and developers should work with these groups to decide how to

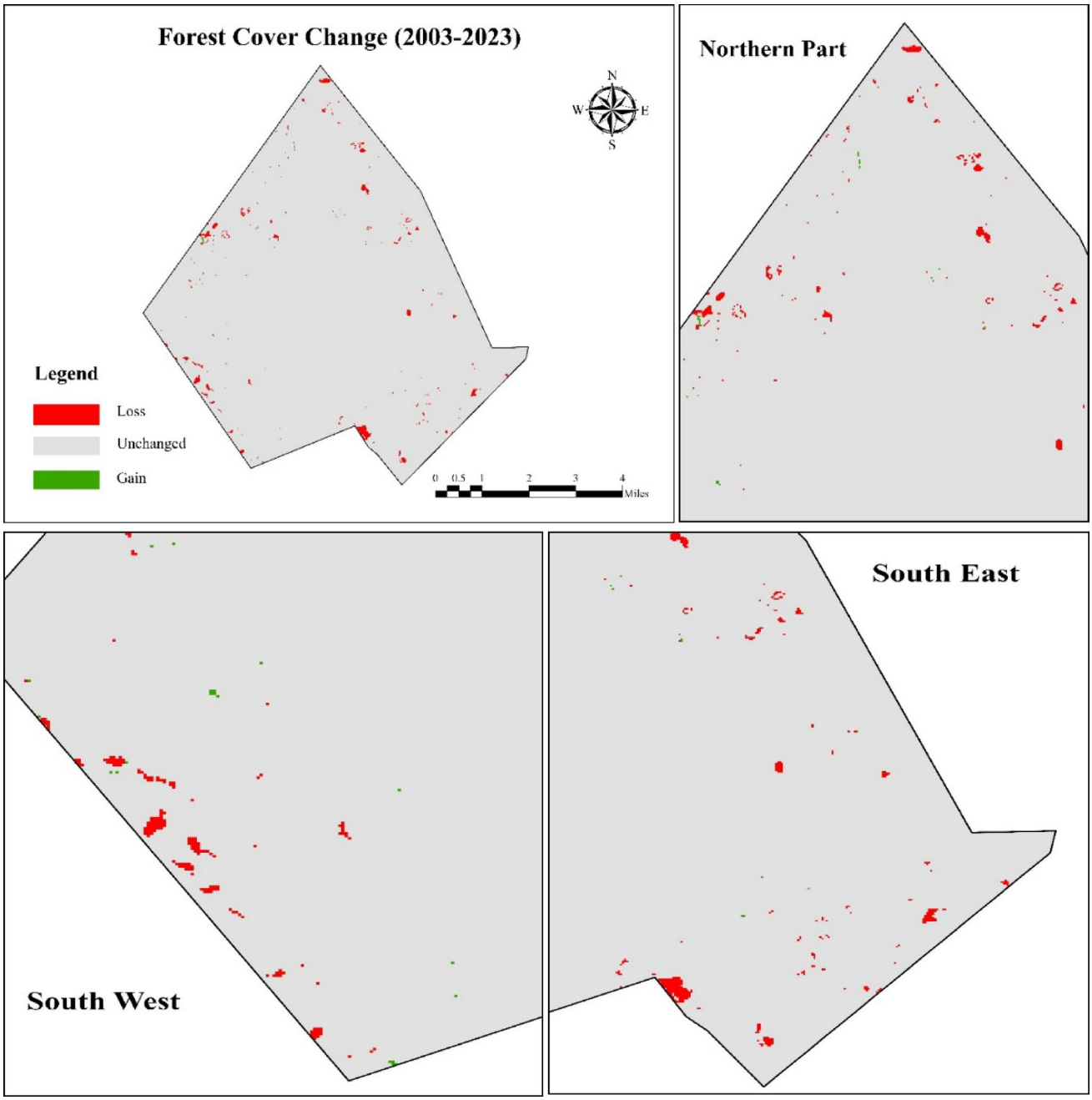


Fig. 10 Spatial changes of forest cover from 2003–2023: Loss, gain & unchanged

Table 4 Predicted LULC area statistics (2033, 2043, and 2053)

LULC Classes	2033		2043		2053	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Waterbodies	2.60	2.59	2.60	2.59	2.60	2.59
Build-up Area	83.61	83.21	83.70	83.31	83.75	83.35
Barren Land	0.02	0.02	0.02	0.02	0.02	0.02
Forest	11.96	11.90	11.86	11.81	11.82	11.76
Grassland	0.08	0.08	0.08	0.08	0.08	0.08
Wetland	2.21	2.20	2.21	2.20	2.21	2.20

Table 5 Temporal changes 2033–2053

LULC Classes	2023–2033	2033–2043	2043–2053
	Area (km^2)	Area (km^2)	Area (km^2)
Waterbodies	0.062	0.000	0.000
Build-up Area	0.037	0.090	0.050
Barren Land	0.001	0.000	0.000
Forest	-0.050	-0.094	-0.047
Grassland	0.031	0.000	0.000
Wetland	-0.007	-0.005	-0.001

use land in ways that support both the growth of the city and environmental sustainability. The various initiatives adopted by all stakeholders can help create a balance between development and ecosystem protection, making Worcester City more resilient to external challenges. Therefore, we recommend scenario-based modeling for Worcester by integrating (i) policy or zoning constraints (city zoning and overlay districts), (ii) socio-economic growth scenarios by adjusting built-up demand and accessibility consistent with Worcester planning/GIS integration, (iii) climate-risk constraints by limiting development in FEMA NFHL and flood-hazard zones, and (iv) conservation scenarios by restricting transition in MassGIS protected or open-space lands and aligning forest targets with Worcester's Urban Forest Master Plan. Moreover, future research should integrate the LULC framework with SSP-based climate scenario modeling to assess how varying socio-economic pathways and climate-risk conditions may influence land-change demand and spatial allocation.

4 Conclusion

This paper determined land use and forest cover dynamics in Worcester City between 2003 and 2023, the key drivers of these changes, as well as the future projections of land use in 2033, 2043, and 2053. Gradual expansion of built-up areas and reduction in forests as well as grasslands indicate that urbanization is the major driver of land use transformation of the city. Climate change challenges, pest control activities, and invasive species management strategies also added fuel to the forest degradation. However, slight increase in wetlands and the stable nature of waterbodies highlight conservation and land management efforts. The findings of the study represent the complex relationship between climate change, urban growth, and environmental sustainability.

The findings have, therefore, reiterated the central argument of the study that monitoring LULC and forest cover changes is very important in maintaining a balance between urban development and ecology. While the landscape of Worcester has been highly modified by urban growth, forest

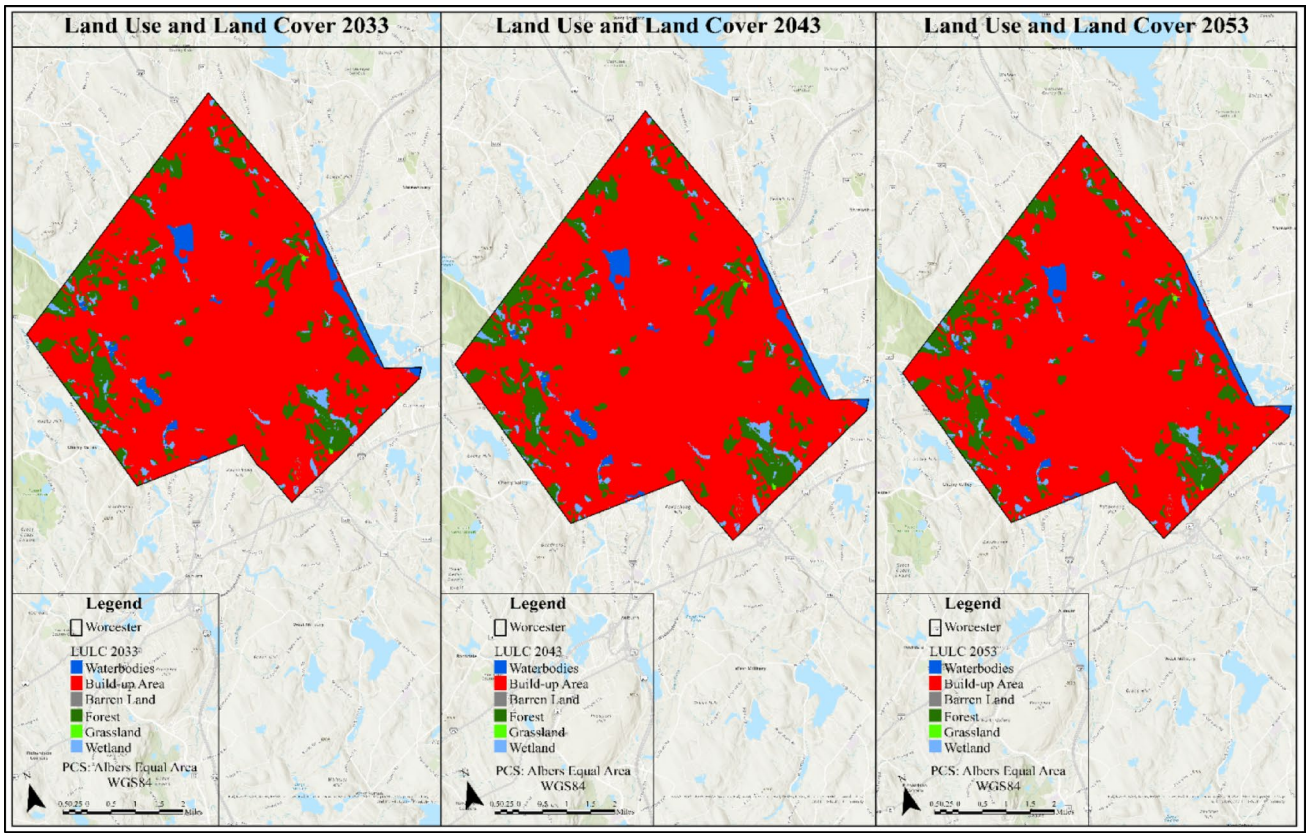


Fig. 13 Predicted LULC map for 2033, 2043 and 2053

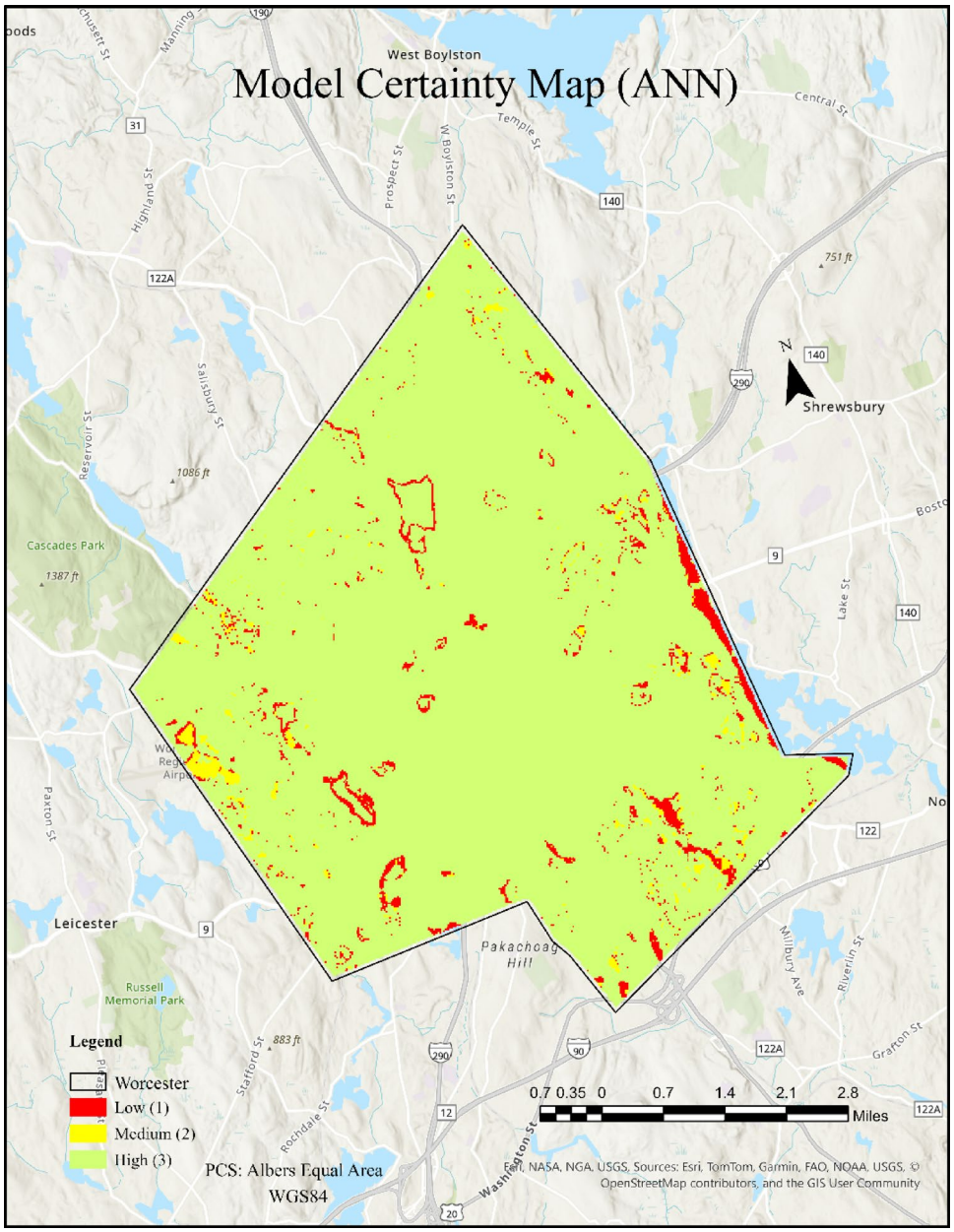


Fig. 14 Class-wise model certainty

restoration and conservation strategies encourage sustainable urban planning and management. By incorporating such types of LULU dynamics and forest cover change detection into decision making process, Worcester City can tackle the challenges like illegal development, habitat degradation and the effects of climate change and urban heat island. Finally, the study offers a framework that can guide other regions facing similar challenges and highlights the need for targeted strategies for sustainable urban development.

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Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

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