

Geospatial Modelling of the Spatial Patterns of Landscape Dynamics of Chennai Metropolitan in South India

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Abstract

Urban sprawl presents significant challenges due to the complex interactions among environmental variables and driving forces that continuously reshape landscape patterns and biodiversity. This study assesses and predicts urban sprawl in Chennai, India, using advanced geospatial modeling techniques. It evaluates land use/land cover (LULC) changes over a five-year period and identifies the major drivers of these changes using high-resolution geospatial datasets. The methodology includes the selection of the study area through Multi-Criteria Decision Analysis (MCDA), the development of multi-temporal land use maps, and the prediction of urban sprawl for 2021 using MOLUSCE (Modelling Land Use Change with Cellular Automata and GIS) and the Land Change Modeler (LCM). Additionally, the study examines several geospatial modeling approaches—such as operations research, system dynamics, agent-based modeling, and geospatial analysis—commonly used in rapidly urbanizing and peri-urban landscapes. Ten primary LULC classes (water, trees, flooded vegetation, crops, built-up area, bare ground, snow/ice, and rangeland) were mapped using ESA Sentinel-2 imagery at a 10-meter resolution for the years 2017–2021. The analysis identifies urbanization, population growth, socio-economic development, and climate change as key drivers of LULC transformations in the Chennai Metropolitan Region. The findings underscore the need for robust geo-based modeling frameworks and integrated landscape planning support systems to strengthen policy formulation, urban planning, and sustainable development efforts in the region.

Keywords: Urban Sprawl, Land Use/Land Cover Change, Geospatial Modeling, Chennai, MOLUSCE, Land Change Modeler, Multi-Criteria Decision Analysis, Landscape Dynamics, Urbanization, Remote Sensing

Urbanisation, urban sprawl, landscape metrics, spatial metrics, remote sensing

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Introduction

Landscape systems have experienced rapid and extensive transformations in recent decades, primarily driven by enhanced accessibility, accelerated urbanisation, expanding globalisation, and an increasing incidence of natural disasters (Lakshmipathi et al., 2025; Verma, Zawadzka & Garg, 2023). Socioeconomic transitions, regional development pressures, and shifts in agricultural and industrial policies further intensify these changes, contributing to the dynamic and often complex nature of landscape modification. Such continuous transitions highlight the necessity for systematic landscape monitoring and robust assessments of spatial pattern changes over time (Kanav et al., 2024).

Understanding the underlying forces that shape landscape change is essential for sustainable natural resource management. The interaction between landscape spatial patterns and ecological processes provides critical insights into how landscape modification affects ecosystem functioning, biodiversity, landscape complexity and fragmentation, and associated cultural practices (Sharma et al., 2025). Quantitative evaluation of landscape transformation—incorporating both structural configuration and ecological implications—is therefore fundamental to landscape research. Anthropogenic interventions often introduce sharp spatial contrasts within otherwise uniform environments, generating micro-heterogeneity that aggregates into macro-heterogeneous patterns typical of many contemporary landscapes (Girish et al., 2024).

Moreover, landscapes respond differently across spatial and temporal scales as they adapt to evolving environmental conditions and disturbance regimes. Developmental pressures and human-induced disruptions can lead to rapid shifts in landscape composition and structure, presenting considerable challenges for understanding the magnitude and direction of urban landscape dynamics (Das & Mandal, 2024). Given their ecological, economic, and sociocultural importance, landscapes serve as a crucial foundation for informed planning, policy formulation, and sustainable management.

Urban landscapes, in particular, are shaped by demographic attributes, population density, occupational structures, and access to essential services. In India, urban areas are often classified based on a combination of population size, population density, and the proportion of non-agricultural workforce (Census of India, 2011). With rapid urban population growth and sustained rural-to-urban migration, many cities continue to witness fast expansion of urbanised regions (Ganguly & Patel, 2025). Since the onset of industrialisation, advancements in transportation networks have further accelerated urban expansion, manifesting in phenomena such as urban sprawl, suburbanisation, edge-city development, the emergence of urban fringes, and exurban growth (Kumar et al., 2025). These trends collectively illustrate the increasing complexity of urban landscape evolution.

Within this context, a comprehensive understanding of landscape dynamics under expanding anthropogenic pressures is vital for achieving sustainable development outcomes. This study therefore investigates the spatiotemporal patterns of landscape change in the Chennai Metropolitan Area. The specific objectives of the study are: (i) to analyse landscape dynamics using multi-resolution spatial and temporal datasets; (ii) to quantify landscape change using landscape metrics and associated landscape parameters; (iii) to model landscape dynamics based on these parameters to identify dominant growth patterns and transformation processes; and (iv) to model and spatially interpolate landscape metrics using geostatistical techniques to support predictive assessment and spatial pattern evaluation.

To support and contextualise this work, we draw on recent studies from across India and other rapidly urbanising regions that have applied multi-temporal remote sensing, GIS-based analyses, landscape metrics, and statistical or geospatial modelling to document urban expansion, land-use/land-cover (LULC) transformation, fragmentation, peri-urban growth, urban sprawl, and associated ecological consequences (e.g., Lakshminpathi et al., 2025; Verma et al., 2023; Ganguly & Patel, 2025; Kanav et al., 2024; Sharma et al., 2025).

1. Study area

The Chennai Metropolitan Area (CMA) is located on the Coromandel Coast as well as covers three districts in the current research, covering Chennai and regions of Thiruvallur and Kancheepuram. CMA is comprised of 176 km² of Chennai district, 637 km² of Thiruvallur district including Ambattur, Tiruvallur, Ponneri, and Ponnammallee taluks, and 376 km² of Kancheepuram district including Tambaram, Sriperumbudur, and Chengalpattu taluks (<http://www.cmdachennai.gov.in/index.html>). It covers an area of 1189 km². The Housing and Urban Development Department had proposed to expand the boundary of the CMA to 8878 km², which would include the whole districts of Thiruvallur, Kancheepuram, and Arakkonam, as well as the Nemili Taluks in Vellore. The Chennai district has a coastline length of 19 kilometers, while the CMA seems to have a total coastal length of 46 kilometers. With a population density of 26,553 persons per km², Chennai is the most densely inhabited city in Tamil Nadu. Chennai is Southeast India's major commercial and industrial metropolis, as well as a cultural, economic, academic, and information technology (IT) hub. The automobile industry, software services, hardware manufacturing, healthcare, and financial services account for the majority of Chennai's economy. It is also known as the "Detroit of India," due to its strong automotive sector. The study region has witnessed substantial development during the last two decades as a result of the expansion in the industrial, car, electronic, as well as tourism sectors.

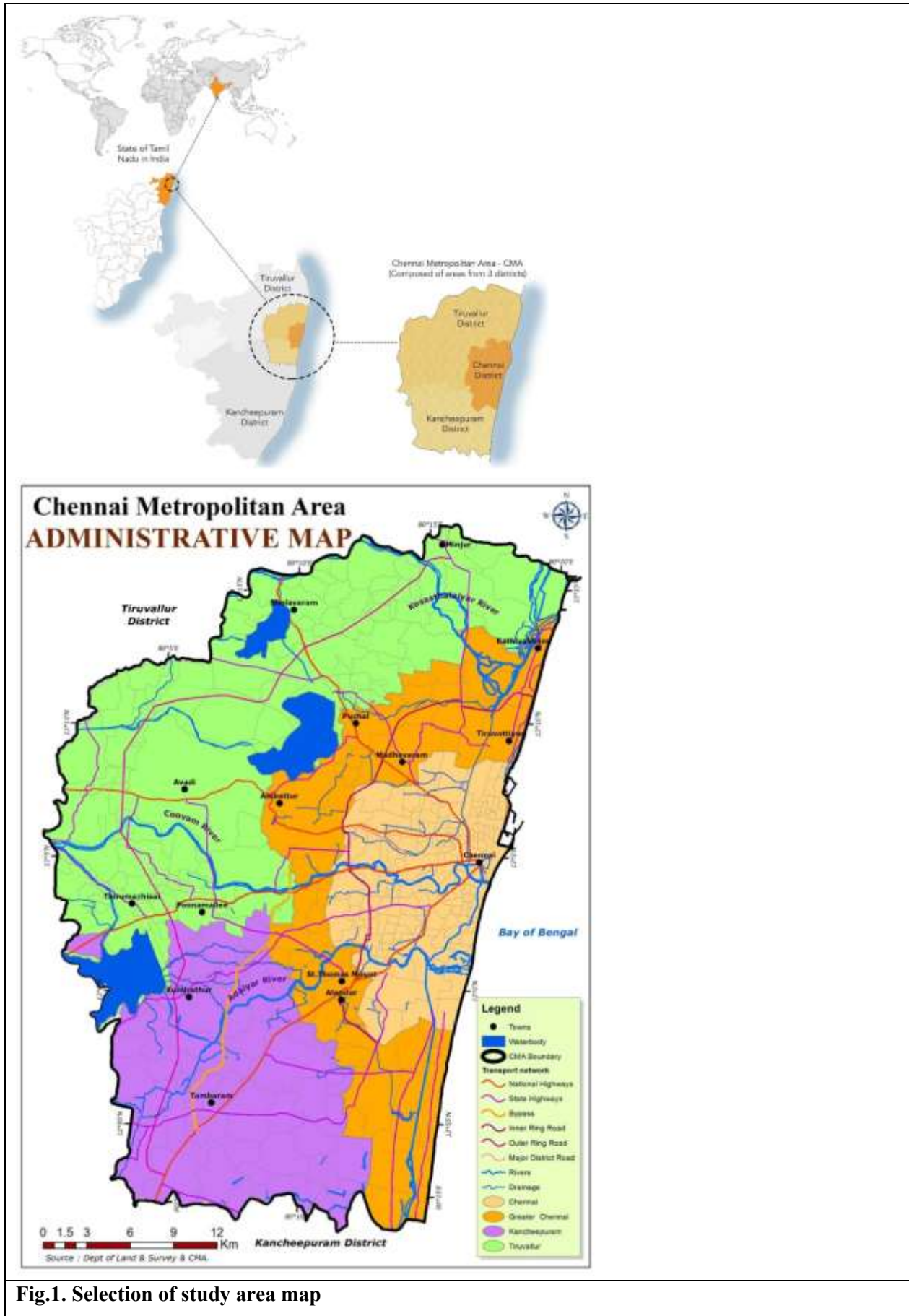


Fig.1. Selection of study area map

2. Materials & Methods

3.1 Data analysis

The remote sensing datasets were geo-referenced, geometrically corrected, and clipped to match the spatial extent of the study area. Geo-registration of the Sentinel-2 MSI imagery was performed using ground control points (GCPs) collected during field surveys with a pre-calibrated GPS, as well as from identifiable reference features such as road intersections obtained from geo-referenced Survey of India topographic maps. Sentinel-2 MSI images from 2017 to 2021, with a high spatial resolution of 10×10 m, were utilized for the analysis. The imagery was further corrected for SLC-off effects using standard image enhancement procedures and nearest-neighbor interpolation. For urban growth prediction, the MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS was employed. A combination of multispectral satellite datasets and relevant driving factors served as inputs to model and forecast urban expansion for the year 2050.

3.2 Land use and land cover analysis

The method involves i) generation of False Colour Composite (FCC) of remote sensing data (bands – green, red and NIR). This helped in locating heterogeneous patches in the landscape ii) selection of training polygons (these correspond to heterogeneous patches in FCC) covering 15% of the study area and uniformly distributed over the entire study area, iii) loading these training polygons co-ordinates into pre-calibrated GPS, vi) collection of the corresponding attribute data (land use types) for these polygons from the field. GPS helped in locating respective training polygons in the field, iv) supplementing this information with Google Earth, v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

Land use analysis was carried out using a supervised pattern classifier - Gaussian maximum likelihood algorithm. This has been proven a superior classifier as it uses various classification decisions using probability and cost functions (Duda et al., 2000). Mean and covariance matrix are computed using an estimate of maximum likelihood estimator. Accuracy assessment to evaluate the performance of classifiers (Gao and Liu, 2008), was done with the help of field data by testing the statistical significance of a difference, and computation of kappa coefficients (Congalton et al., 1983; Sha et al., 2008) and proportion of correctly allocated cases (Gao & Liu, 2008). Recent remote sensing data (2021) was classified using the collected training samples. Statistical assessment of classifier performance based on the performance of spectral classification considering reference pixels is done which includes computation of kappa (κ) statistics and overall (producer's and user's) accuracies. For earlier time data, training polygon along with attribute details were compiled from the historical published topographic maps, vegetation maps, revenue maps, etc.

Application of maximum likelihood classification method resulted in accuracy of 76% in all the datasets. Land use was computed using the temporal data through open source program GRASS - Geographic Resource Analysis Support System (<http://grass.fbk.eu/>). Land use categories include i) area under vegetation (parks, botanical gardens, grass lands such as golf field.), ii) built up (buildings, roads or any paved surface, iii) water bodies (lakes/tanks, sewage treatment tanks), iv) others (open area such as play grounds, quarry regions, etc.).

3.3 Calculation of Landscape Metrics

Landscape metrics provide a quantitative description of the composition and configuration of the urban landscape.

3.4 Principal Component Analysis

Principal component analysis (PCA) is a multivariate statistical analysis that aids in identifying the patterns of the data while reducing multiple dimensions. PCA through Eigen analysis transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible (Wang, 2009). PCA helped in prioritizing eight landscape metrics based on the relative contributions of each metrics in the principal components with maximum variability which helped in prioritizing Landscape metrics.

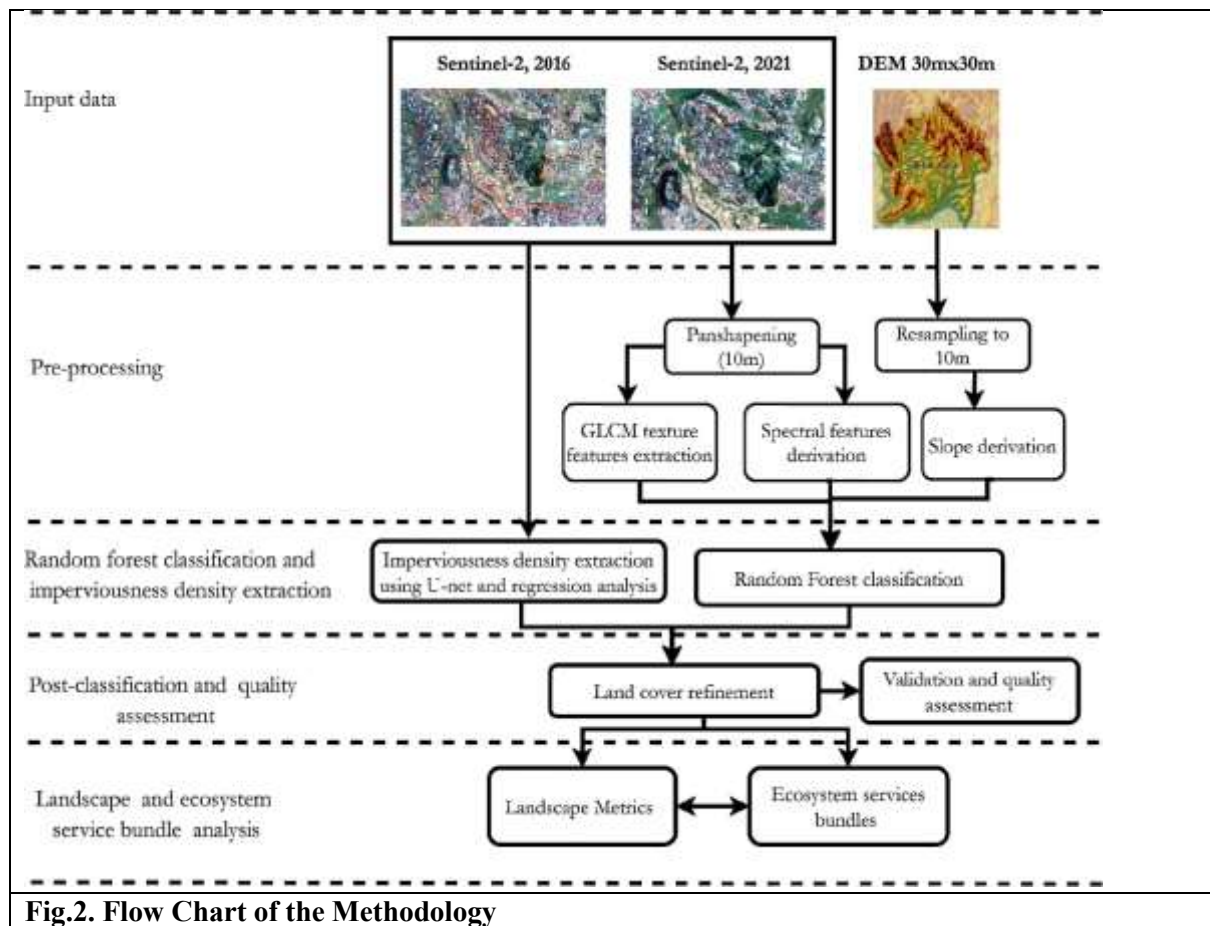


Fig.2. Flow Chart of the Methodology

4 Results and Discussion

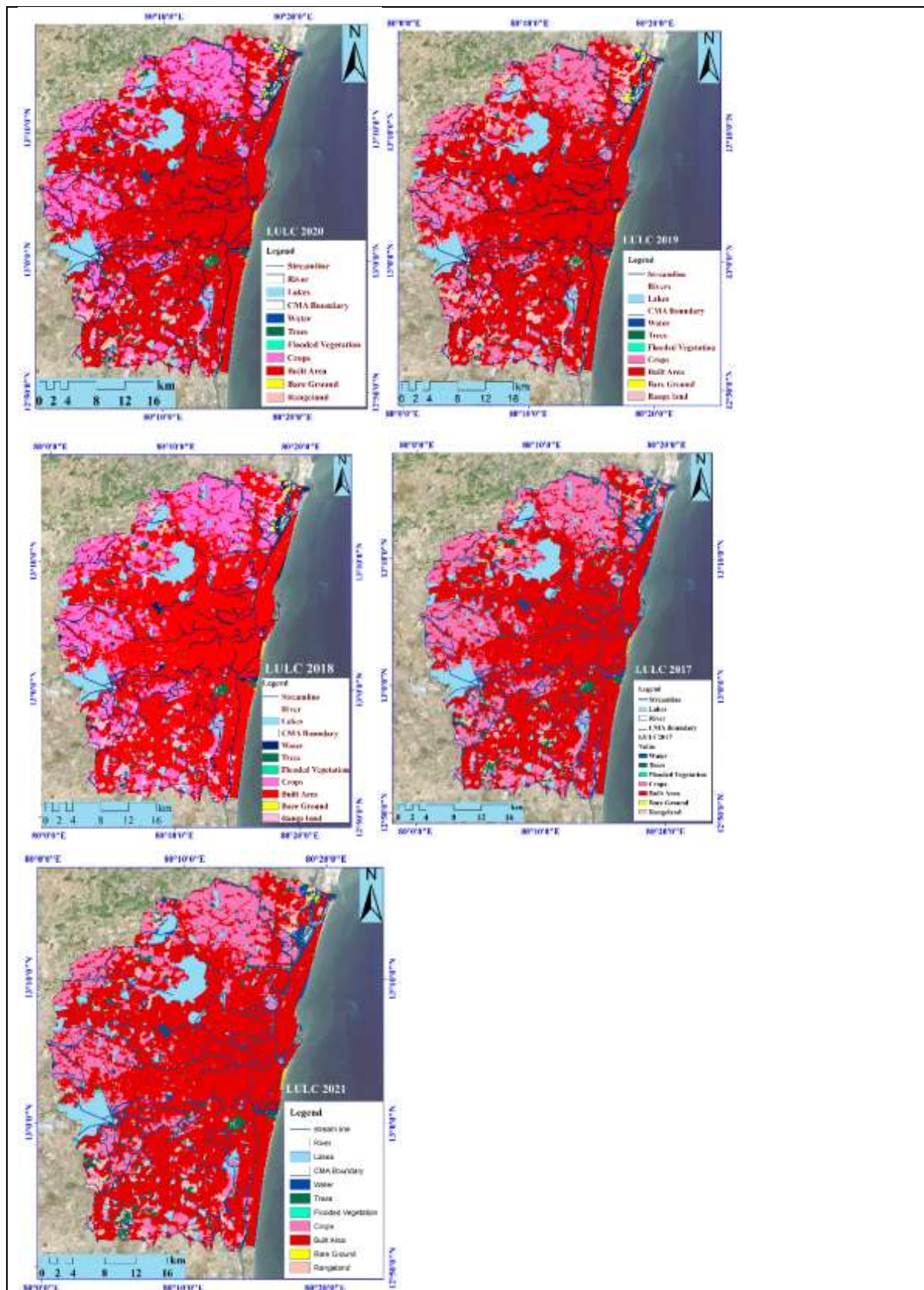
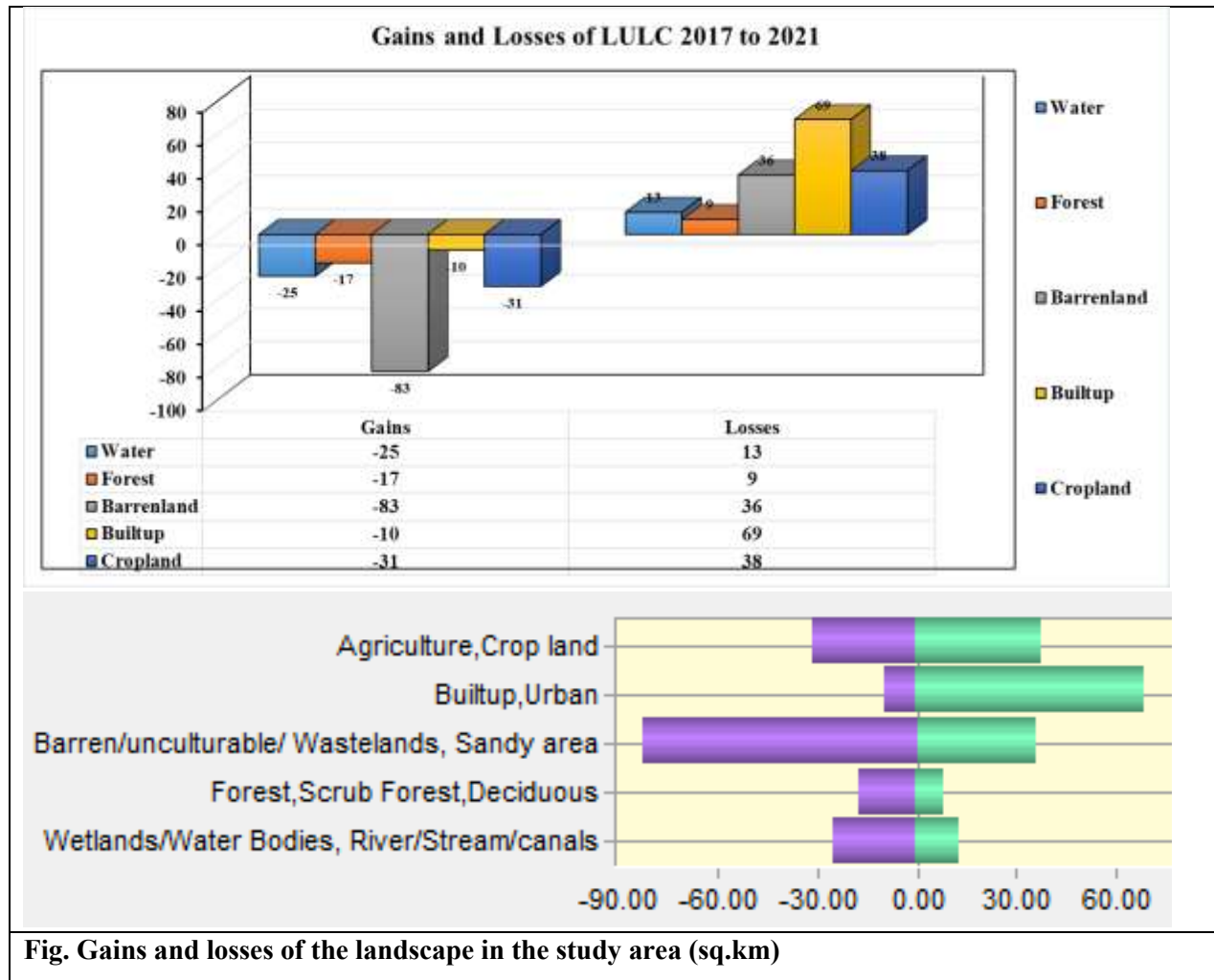
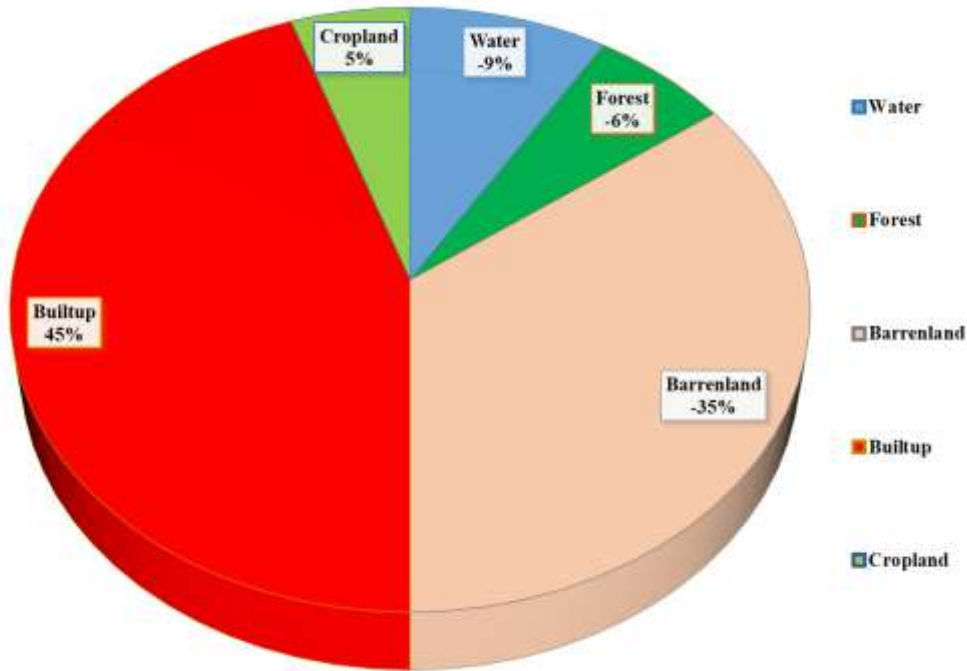


Fig.3. Land use land cover classification using maximum likelihood classification maps of 2017 to 2021

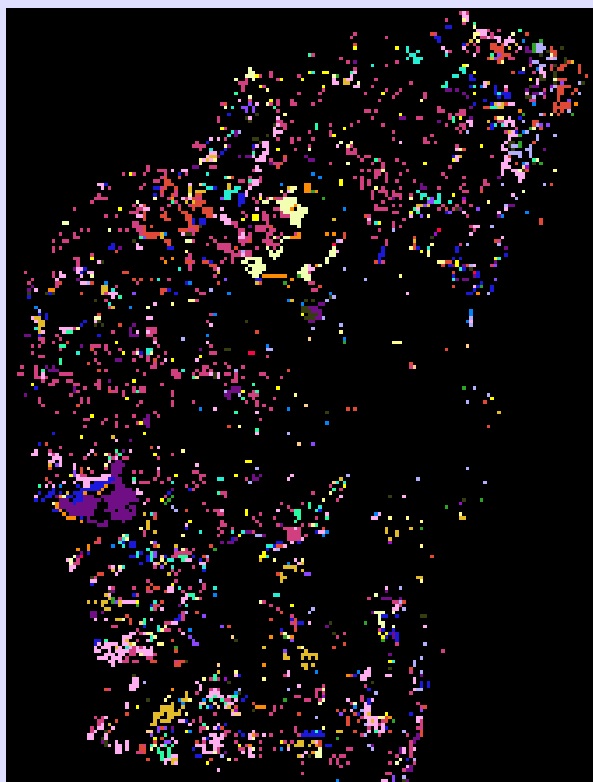
Models

An urban growth model is a particular type of numeric model that involves economics, geography, sociology, and statistics to explore the mechanisms of urban evolution and feedback of the urban system. A better understanding of the urban growth process and its effect on the environment is essential for efficient urban management.



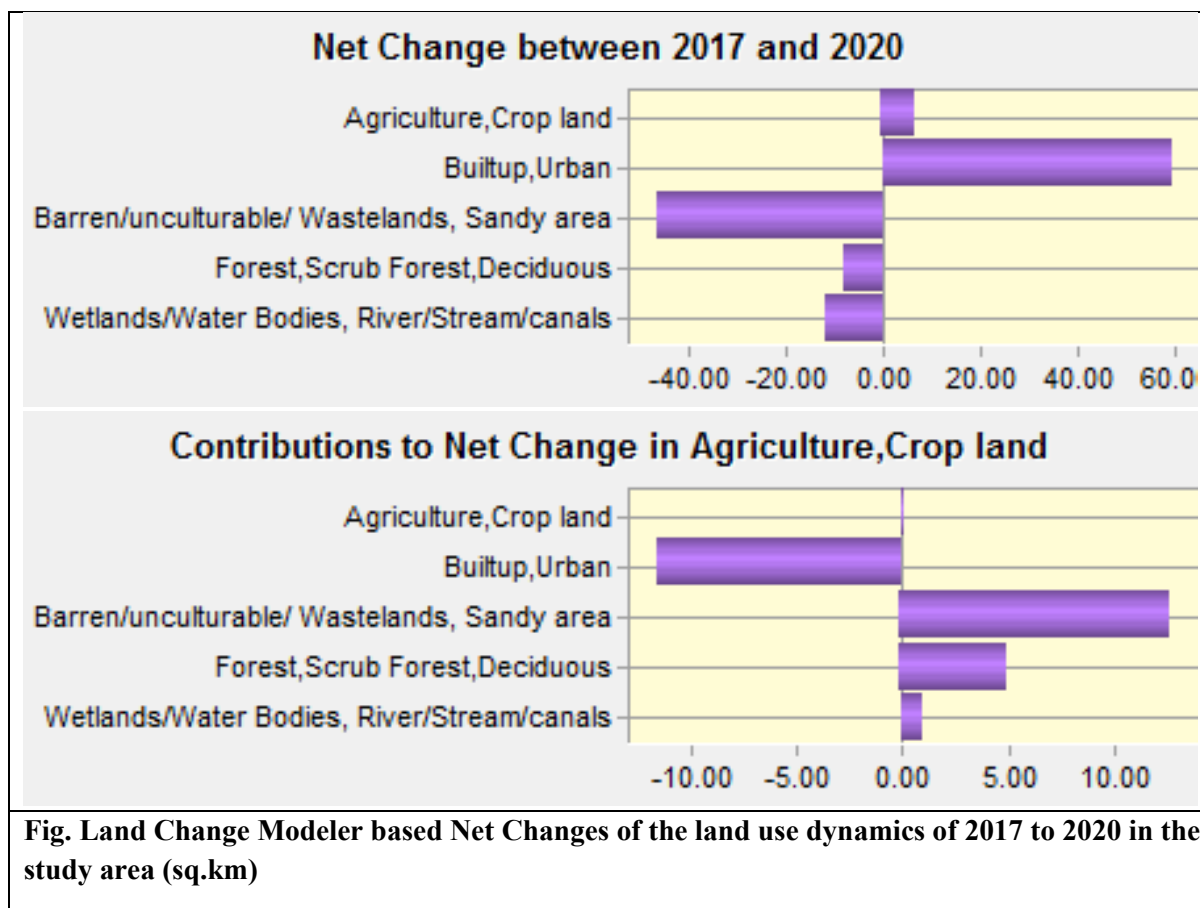


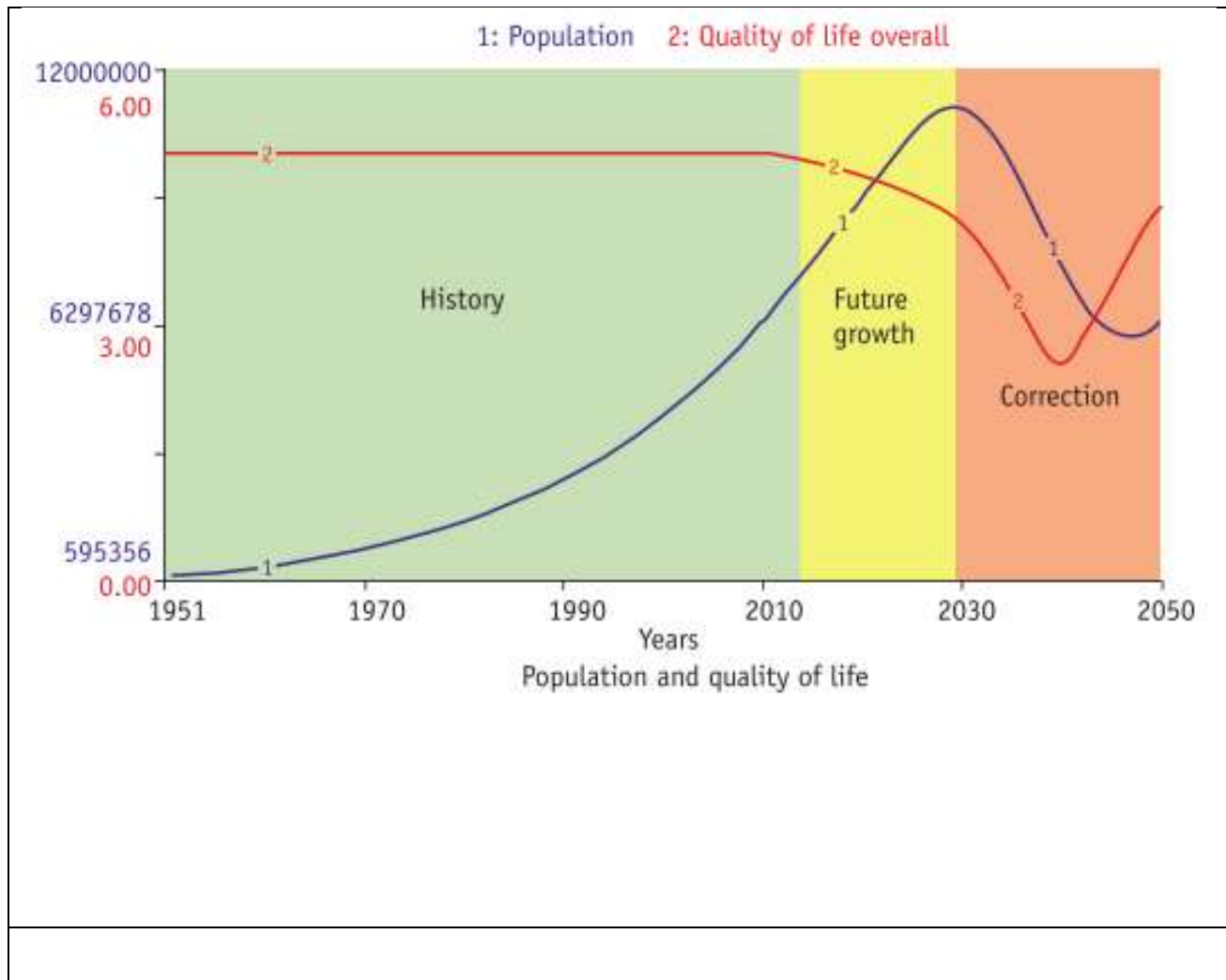
Change from 2017_LCM to 2020_LCM



- Forest to Water
- Barrenland to Water
- Builtup to Water
- Cropland to Water
- Water to Forest
- Barrenland to Forest
- Builtup to Forest
- Cropland to Forest
- Water to Barrenland
- Forest to Barrenland
- Builtup to Barrenland
- Cropland to Barrenland
- Water to Builtup
- Forest to Builtup
- Barrenland to Builtup
- Cropland to Builtup

Fig. Area change statistics of the Land use patterns in the study area





5 Conclusion

Urban sprawl prediction models can help us effectively in quantifying future urban sprawl growth and also identify direction and pattern of urban sprawl growth. This approach can help in urban planning and good governance. Also, it helps in resource management as identifying urban sprawl growth can also provide information about quantifying increased demand of the resources correctly.

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