APPLICATION OF REMOTE SENSING AND GIS IN ASSESSING LAND USE LAND COVER CHANGES IN MORSHI TALUK, MAHARASTRA, INDIA

Abstract

The rapid growth of the population and human activities on Earth is significantly altering the natural environment. Consequently, this paper endeavours to assess and delineate changes in Land Use/Land Cover in Morshi Taluk, Amravati District. The research was focused on application of remote sensing and GIS in assessing LULC changes in Morshi Taluk from the years 2014 to 2022. The LULC maps for these years were generated through supervised classification, employing both the maximum likelihood algorithm and a multi-sectoral supervised classification algorithm tailored to Landsat sensor data. The Extract by Mask tool was employed to isolate the desired location, followed by the application of image classification tools using various band combinations, such as false-colour composite (5,4,3). The classification scheme for LULC was executed based on Landsat 8 TM satellite images. Research found that major changes happened in urban area, water body, agriculture area and waste land. Here, in 2014, the built-up area constituted 1.67% of the total land, experiencing an increase of approximately 0.7% by 2022. Over the decade, the agricultural (crop land) area decreased by 2.98%, while waste land, representing 4.96% of the total area in 2014, increased by nearly 0.34% by 2022. The water body, constituting 3.94% of the total area, increased by almost 1.94% over the same period. Analysis of LULC trend of Morshi will help to understand and take necessary action to the line department to reduce the impacts of LULC changes as well as provide change scenario and which will be help to appropriate land use planning and management of Morshi Taluk.

Keywords: Land use-Land cover, supervised classification, RS &GIS, Morshi Taluk.

Introduction

The Land Use and Land Cover change detection assessment are concerned of scientists worldwide for realizing the importance of the land resource to achieve environmental security and sustainable development (Tewabe and Fentahun 2020). At present, the LULC pattern's changing scenario has become an immense issue for utilizing our natural capital and resources. Here, land use refers to human activity on the earth's surface such as infrastructure building, agricultural cropping and land cover refers to natural or manmade physical properties of the earth surface such as water body, vegetation covers etc. Change detection involves identifying alterations in the state of an object or phenomenon through repeated observations. The crucial aspect lies in the ability to measure temporal impacts using multi-temporal datasets ((Akpoti et al., 2016; Bewket, 2002; Hurni et al., 2005). Remotely sensed data from Earth-orbiting satellites is extensively employed for change detection due to its repetitive coverage at frequent intervals and consistent image quality.

The rapid changes in LULC associated with urban growth are primarily attributed to the city's expansion. Over the last few decades, Earth's terrestrial surfaces have undergone significant transformations due to the global trends of economic expansion and population growth. The concentration of people in urbanized societies during the 19^{th} and 20^{th} centuries resulted in the development of cities. The migration of villagers to cities is influenced by the area's appeal for a higher quality of life and new employment opportunities (Geremew, 2013). While humans have been modifying the land for thousands of years to meet their needs, the current rates, extents, and intensities of LULC change surpass any other period in human history. This has led to unprecedented alterations in ecosystems and environmental processes at local, regional, and global scales. The major environmental challenges facing the human population today, such as climate change, biodiversity loss, and water, soil, and air pollution, are all influenced by changes in land use and cover. Researchers and policymakers globally now prioritize monitoring and mitigating the adverse effects of land use and land cover change while ensuring the sustainable production of key resources (Patra et al, 2018)

Satellite images are the most common data source for mapping LULC formation (Vanjare et al., 2014). Satellite image provides the geo-referenced raw pictures (Leprince et al., 2007). Thematic Mapper (TM) imagery is used for land cover mapping (Zhao, et al., 2004). The changes in the land cover of the study area are analysed by land cover map using satellite images (Talukdar et al, 2020; Mishra et al, 2020). By using multi-date images, it is possible to changed detection and also monitors and evaluates the use of land cover due to human actions and natural conditions ((Hegazy and Kaloop, 2015; Solaimani et al., 2010). In this study used Landsat 8 (OLI_TIRS) satellite images from 2014-2022. For monitoring the changing pattern study create LULC map for the selected years by using the method of supervised classification with maximum likelihood algorithm, multi-sectoral supervised classification algorithm to Landsat sensor data and extract by mask tools. Accuracy measurement work are done to validate the research findings and the result is acceptable level.

Morshi, located in the Amravati District of Maharashtra, India, holds the position of the second-largest town and is characterized by ongoing development and a high population density. The Taluk has experienced significant changes in its land area, witnessing the transformation of vast agricultural land, wasteland, and water bodies for the sake of urban growth and development. Given these dynamics, it is crucial to regularly update the current Land Use and Land Cover status of the Taluk. This is essential for effective land use planning, sustainable land management, and overall development, addressing both rural and urban needs (https://environmentclearance.nic.in, 2018).

In light of these considerations, this study focuses on detecting LULC changes and analyzing the impact of urbanization on land resources in Morshi Taluk from 2014 to 2022. The research delves into alterations in urban, rural, residential, industrial (Built-up) areas, as well as changes in agriculture and other land uses. As the demand for land resources continues to rise in proportion to the growing population, understanding and monitoring LULC changes become critical at local and global levels. The findings of this study contribute to current strategies for managing natural land resources and monitoring environmental changes. Ultimately, such LULC change detection studies are imperative for sustainable environmental planning and management, ensuring the survival and well-being of human communities.

Objectives:

The present research study has the following objectives

1. To Create LULC mapping from satellite images of 2014
2. To Create LULC mapping from satellite images of 2022

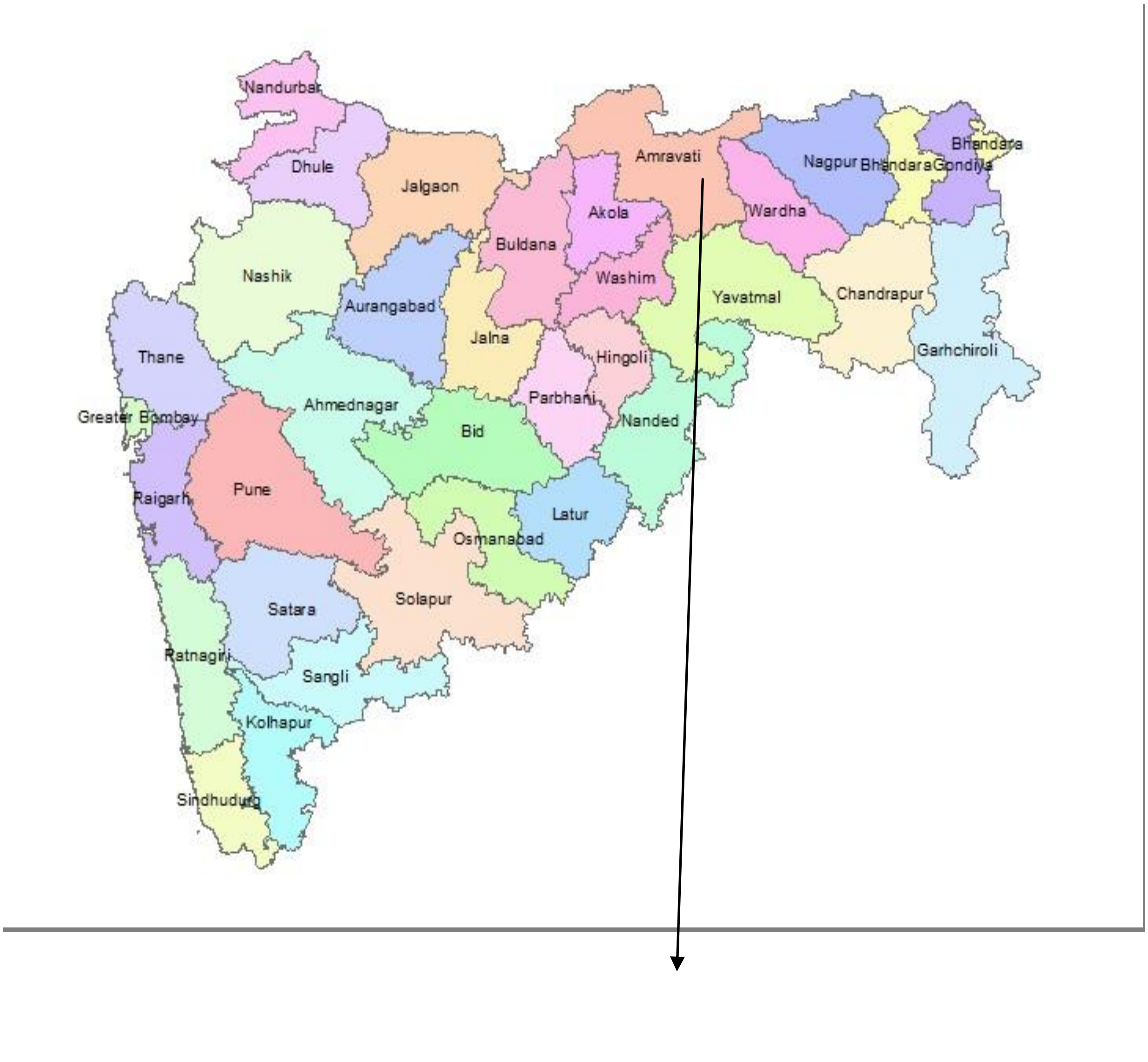
Materials and methods

Study area

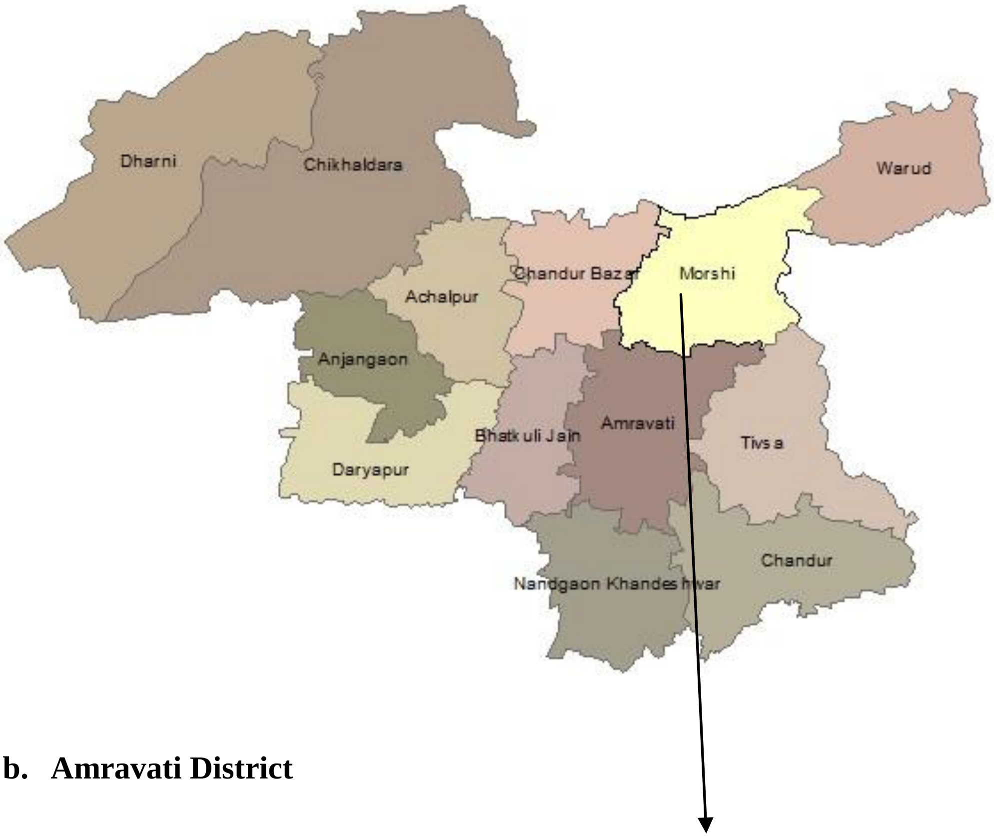
Morshi, situated in Morshi Taluka within the Amravati District of Maharashtra State, India, is part of the Vidarbha region and falls under the Amravati Division. Positioned 60 kilometers to the north of the district headquarters, Amravati, it serves as a Taluka headquarters, covering an area of 809.10 sq.km between 21° 14' 16" to 21°25' 23"N latitude and 77°07' 44" to 77°53'24"E longitude (Fig. 1). Known for the cultivation of Nagpur Oranges, Morshi and its surrounding region are also distinguished by the prominent Nal Damayanti Dam, with Salbardi in close proximity (https://environmentclearance.nic.in, 2018).

As per the 2001 Indian Census report, Morshi's population was recorded at 33,607, with males constituting 51% and females making up the remaining 49%. Among the population, 12% are children under six years of age. Morshi boasts an average literacy rate of 78%, surpassing the national average of 59.5%. The male literacy rate stands at 82%, while the female literacy rate is 73% (https://environmentclearance.nic.in, 2018).

The region experiences rainfall primarily during the south-west monsoon, with about 90% occurring between June and September. The Taluka witnesses a long-term normal rainfall of 961 mm, displaying a coefficient of variation of 28%. Maximum temperature reaches around 28.4 degrees Celsius, while the minimum temperature hovers at 12.3 degrees Celsius. Maximum Relative Humidity is expected to be 44%, with the Minimum Relative Humidity at 22% (https://maharain.maharashtra.gov.in; https://data.gov.in/catalog/rainfall-india).



a. Maharashtra state



b. Amravati District

Figure 1: study area map (Morshi Taluk)

Datasets

The study utilized Landsat 8 OLI/TIRS C2 Level-2 Images for the years 2014 and 2022, featuring a spatial resolution. These images were obtained freely from the Landsat archive on the United States Geological Survey (USGS) website, accessible through (https://glovis.usgs.gov/in) and (https://earthexplorer.usgs.gov/in) (Zimale et al., 2018; Gutman et al., 2008). The Landsat data underwent both visual and digital interpretation using ArcGIS 10.8 software, employed for the processing, analysis, and integration of spatial data.

Data Preparation

In this study, Image processing and visual interpretation techniques were employed for Land Use/Land Cover classification using digital data and standard False Colour Composite (FCC) satellite images. The classification involved the utilization of a Standard False Colour Composite (FCC) for Landsat TM images, mapping land use/land cover for the years 2014 and 2022. The interpretation process considered aspects such as shape, size, tone/colour, texture, pattern, and location of specific features on the satellite imagery. Land Use/Land Cover maps were generated using the supervised classification method with the maximum likelihood algorithm (Rawat and Kumar, 2015). The land cover maps for the selected years were created by applying a multi-sectoral supervised classification algorithm to Landsat sensor data (Lucas et al., 2007). Landsat 8 (OLI_TIRS) satellite images, featuring seven and eleven bands respectively, were converted into an image using composite bands (Zha et al., 2003). The supervised classification process involved basic methods such as composite band creation, raster copying, cloud removal, mosaic to new raster, extraction by mask, and maximum likelihood image classification (Su et al., 2010; Persello and Bruzzone (2012). These processes were executed using ArcMap 10.8® software.

The copy raster function was used to eliminate the background of images, rendering a transparent background, serving as a pre-processing step for image classification. Haze reduction was addressed in this phase, and the image enhancement technique employed histogram equalization. Cloud cover and haze conditions were deemed acceptable, as they were minimal across all images. To create an accurate aerial representation of the study area, the study utilized image mosaic to a new raster in ArcMap 10.8® software, consolidating Landsat images into one comprehensive representation (Hood and Bayley, 2008). The extract by mask tool was employed to isolate the desired location (Magesh and Ch, 2012).

Image classification

In this study, images underwent classification into four major classes: water bodies, built-up (urban areas), barren soil (wasteland), and crop land. The standard "false-color" composite for Landsat 8 TM satellite images, comprising bands 5, 4, and 3, was employed (Mahendra and Mallikarjunaswamy 2022; Tamouk et al., 2013). For Landsat 8 TM false-color composite in Natural Color (bands 4, 3, 2), which closely resembles what the human eye perceives, greenery appeared as green, with healthier vegetation appearing brighter. Urban features appeared white and dark, and water displayed as dark blue or black (Elhag, 2017; Mwaniki et al., 2015; Tamouk et al., 2013; Dwivedi and Rao, 1992; Yuan and Zhu 2018). To facilitate the selection of pixels for each land use and land cover category, a substantial number of pixels were chosen in this study. Ultimately, the maximum likelihood supervised image classification method was applied using ArcGIS software (Gomez et al., 2016; Lu and Weng, 2007).

Change detection:

Change detection analysis involves a diverse array of methods employed to recognize, characterize, and quantify disparities between images of the same scene captured at distinct times or under varying conditions. Many of these tools can be utilized either independently or in combination, forming part of a comprehensive change detection analysis (Han et al., 2009). The change detection process typically follows a straightforward approach, measuring alterations between a pair of images representing an initial stage and a final stage. Change detection statistics, often averaging classification images, are commonly employed to compute the difference map for the images.

Results and Discussion

Applying the maximum likelihood and multi-sectoral supervised classification algorithm, Land Use/Land Cover maps for the years 2014 and 2022 are presented in Table 1 and Figure 2 Figure 3, respectively. In 2014, the built-up area constituted 1.67% of the total land, and it experienced an increase of approximately 0.7% by 2022, this finding was similar to (Tekle, 2001). Over the course of 10 years, the agricultural (crop land) area decreased by 2.98%. Waste land, which accounted for 4.96% of the total area in 2014, saw an increase of nearly 0.34% by 2022, similar results observed by (Belay and Mengistu, 2019). Chakravarty et al., 2012 observed that the population growth and urbanization resulted in significant reductions in agricultural land and the study reveals that the urban area expanded by 5.18% from 1990 to 2019. Hasan et al. (2013) noted a more substantial increase in the urban area, from 474.95 to 876.16 km^2 between 2000 and 2010. Hanewinkel et al., 2013 noted Barren soil showed no significant changes from 1990 to 2019 and also in the first 20 years (1990 to 2010), the vegetation area increased by approximately 3.36%, but from 2010 to 2019, this area experienced a decline of 0.9%. The water body, constituting 3.94% of the total area, increased by almost 1.94% over the decade. Rai et al. (2017) observed that decrease in permanent wetlands from 4.15% to 1.16% between 1967 and 2010 in their research paper from 2017. Similar result observed by Islam and Gnauck, 2009; Chatterjee et al., 2015; Mukhopadhyay et al., 2006.

Table 1. Area under different land use / land covers categories during 2014-2022

Land Use Land Cover Classes	**2014 (Ha)**	**Area (%)**	**2022 (Ha)**	**Area (%)**
Built-up	1347	1.67	1907	2.37

Crop land	71875	89.43	69473	86.45
Waste land	3974	4.96	4261	5.30
Water body	3171	3.94	4726	5.88
Total	**80367**	**100**	**80367**	**100**

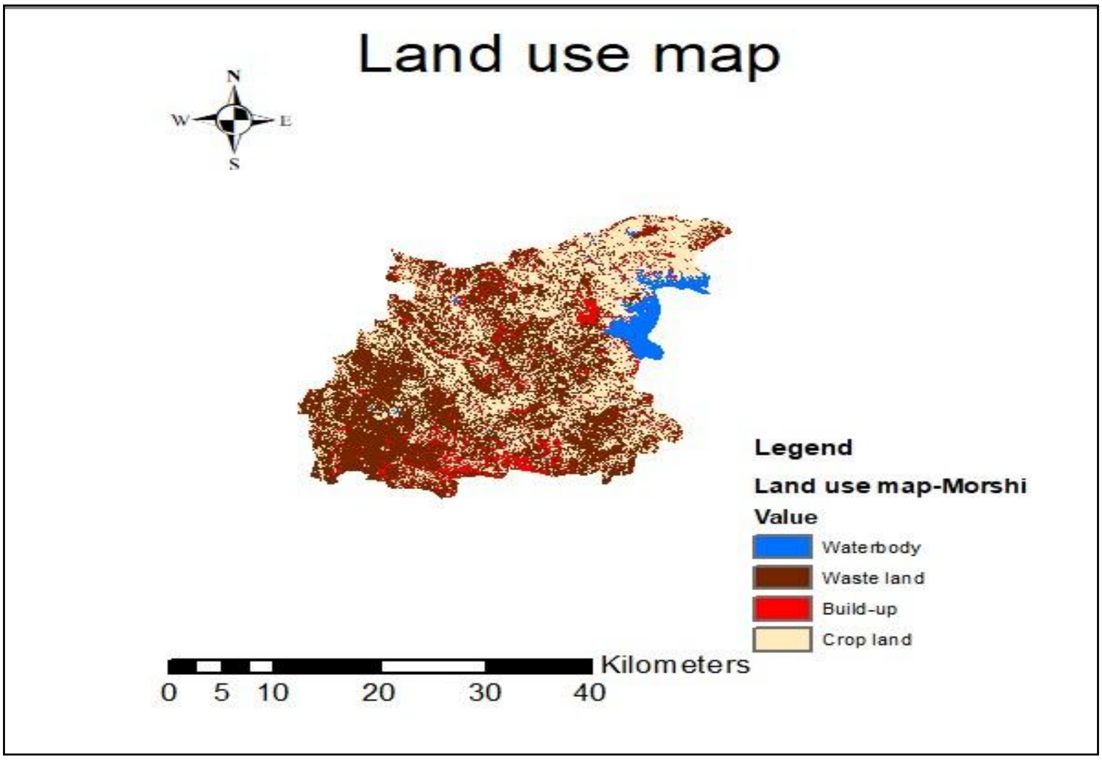


Figure 2. Map showing the Land use categories for the year 2014

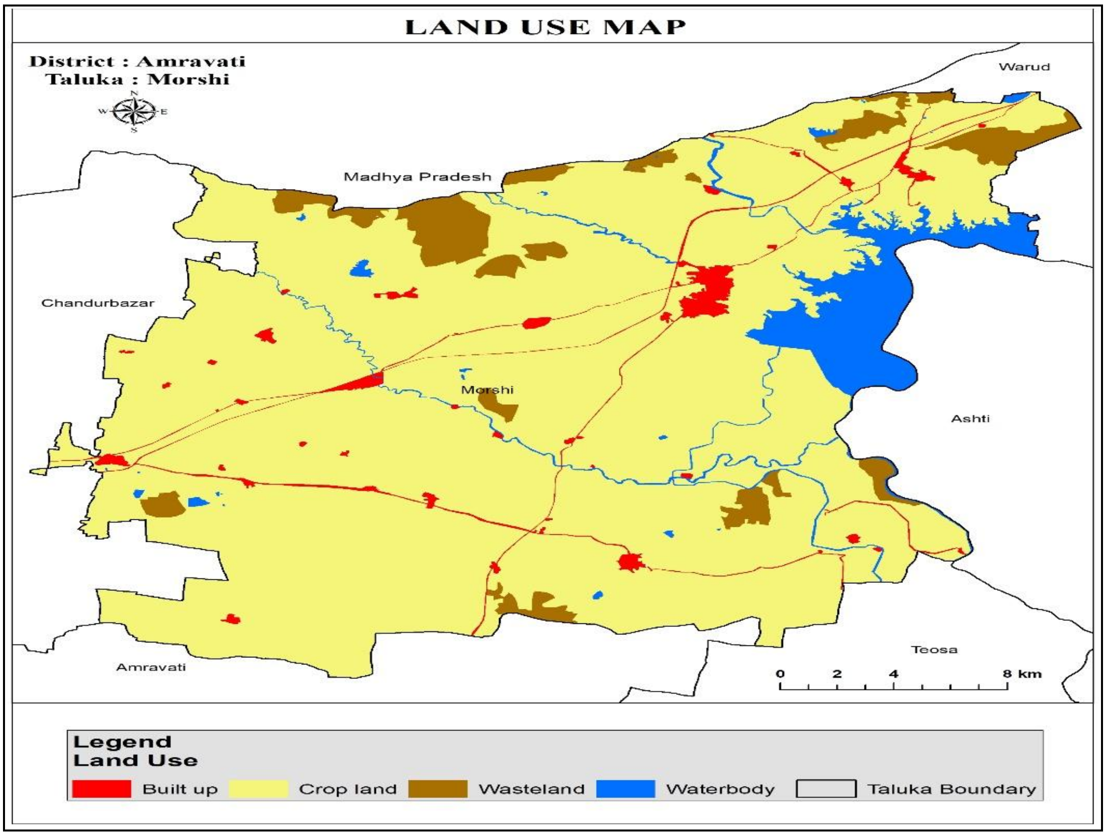


Figure 3. Map showing the Land use categories for the year 2022

Conclusion:

Land is a crucial natural resource essential for sustaining life, and monitoring Land Use/Land Cover changes is instrumental in planning and implementing strategies to conserve land cover. This study leverages Landsat 8 OLI/TIRS satellite images and utilizes ArcGIS software techniques to quantify and calculate land cover changes in Morshi Taluk, Amravati District, from 2014 to 2022. The research identifies that land use changes in the study area have had a significant negative impact on both society and the environment. Rapid urban development has led to a reduction in agricultural land, vegetation. The transformation of agricultural and vegetation areas is attributed to the expansion of residential areas, altering the livelihood patterns of the local population. The use of hybrid seeds and pesticides by farmers to enhance productivity has resulted in environmental pollution. Urbanization has encroached upon water bodies due to overpopulation and development, with water bodies being filled for cultivation and urban purposes. Deforestation for infrastructure needs and fuel further exacerbates the environmental impact. Geographic Information System (GIS) and Remote Sensing (RS) technologies were employed to process and analyze the data, ultimately generating maps. The results offer crucial information to relevant line departments, aiding policymakers, environmental management groups, and the general public in comprehending the changing landscape. The integration of GIS and remote sensing technologies is affirmed as an effective tool for land cover planning and management. The quantification of LULC changes in the Morshi area serves as valuable information for environmental management, facilitating informed decision-making and understanding of the surrounding environment.

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