Land use and land cover changes impacts in the harbour city of Thoothukudi

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Abstract: Population growth directly disturbs the environment for development, suburbanisation, and social changes. Urban growth leads to shrinking agriculture and forest land and has substantial impact on the land and coastal ecosystem. Regular studies on urban sprawl growth modelling and analysis are needed to provide better urban growth and ensure sustainable urban development. The city of Thoothukudi, located in the states of Tamil Nadu, India, has faced rapid population growth and urban extension over the past three decades. Geospatial tools and satellite imagery were employed to investigate previous changes and growth in the urban landscape. Random forest classification was used to study sustainability and urban growth in Thoothukudi city's administrative border and the suburbs within a 15 km buffer zone. The result shows that Thoothukudi experienced rapid urban growth, increasing by 68.42% between 1997 and 2017. The outcome of this study will assist government officials and urban planners to provide a better strategy to reduce the environmental and social consequences, facilitate the development of the city in a sustainable way and protect the ecosystem services in the near future.

Keywords: land use; land cover; urban sprawl.

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1 Introduction

An uncontrolled increasing human population generates migration of people towards nearby cities for an education, work and a better social life. The world population is expected to increase about 72% by 2030. Development in urban areas has led to dramatic changes in the configurations of land use (Foley et al., 2005). In order to facilitate communities with different utilities, government and private sectors have focused on urbanisation and industrialisation. Advances in land use and spatial analysis have led to a better understanding of developing patterns and have helped to create sustainable urban studies (Lambin et al., 2001). Growing numbers of inhabitants lead to land and water scarcity. So, the people often encroach and built settlements in less expensive areas, often on the peripheries of cities. This sudden development leads to urban sprawl and irregular settlements in vegetation and productive lands. Changes in the land have often come about due to various improvements by land users. Changes in land use at any location may involve either shifting of land or intensification of existing land use. These changes may cause some changes in the land cover, but land cover may change even if the land use remains unaltered. The realms of land use and land cover (LULC) are connected in such a way that human activities can alter the environment.

Land cover refers to the observed biotic and abiotic assemblage of the Earth's surface and intermediate subsurface. The term denotes the physical state of the land. It includes quantity and type of surface vegetation, water, and earth materials. Changes in land cover take place in two ways: as conversion and modification. The term conversion refers to change from one class of land cover to another, whereas modification refers to change of conditions within the land cover category. Conversion is easier to measure and monitor than modification using remotely sensed data. Modification, which is a long-term process, requires multiyear and multi-seasonal monitoring for accurate quantification. LULC changes have become central components in current strategies for managing natural resources and monitoring environmental changes. As advancement in the concept of vegetation mapping has greatly increased research on LULC change, providing an accurate evaluation of the spread and health of the world's forest, grassland, and agricultural resources has become an important priority. Viewing the Earth from space is now crucial to the understanding of the influence of humanity's activities on the natural resource base over time. In situations of rapid and often unrecorded land use change, observations of the earth from space provide objective information on human utilisation of the landscape. Over the past years, data from Earth sensing satellites has become vital in mapping the Earth's features and infrastructures, managing natural resources, and studying environmental change. The main objective of classification is to improve the economic condition of an area by implementing sustainable land use systems without deteriorating the environment.

Even though in several studies the degree to which contribution to landscape change differs (Abddullah and Nakagoshi, 2006; Almieda et al., 2008), the formation of new suburbs by cutting productive and wetlands leads to pollution and degradation of land.

The rapid growth of urban sprawl directly affects the ecosystem services of city landscape and its peripherals area by shrinking forest, agriculture and wetlands. Unplanned urbanisation also drives environment and manmade disasters, including floods, drought and health risk, particularly in developing states like Tamil Nadu, India, where 70% of the total population are forecasted to live in cities and suburbs by 2030. The estimation and quantification of urban sprawl and growth of cities is thus vital in order for Tamil Nadu to support development, urban planning and designing, policy making and maintain ecosystem services. However, such studies are scarce for places like Tamil Nadu. While demographic urbanisation has been well-documented, urban expansion is relatively less understood, and comparative studies on urban expansion among different cities are limited (Huang et al., 2007; Schneider and Woodcock, 2008; Wu et al., 2011).

Remote sensing techniques and geographic information systems have shown significant possibilities for urban sprawl and growth analysis and predictions. Changes in landscape have been associated with population growth migration and industrialisation, so the LULC changes studies are the primary indicator for urban sprawl studies. The LULC has the key factor to understand the correlation among human behaviour and environment, which can be competently attained from remote sensing imageries through image classification techniques. The development of landscape ecology in the past few decades has arguably provided a new perspective for urban expansion studies (Berling-Wolff and Wu, 2004; Shi et al., 2012). Urban areas have changed rapidly over the last decade; analyses of urban dynamics have become increasingly common due to the fact that they can be produced rapidly and are easy to use in comparative analysis (Uuemaa et al., 2013). An automatic and semi-automatic image classification is widely used to understand urban growth and urban sprawl. These are mainly advantageous for countries like India, which has vast land and a lack of ground monitoring data. The availability of satellite images from different sensors for different periods assists in modelling decades' worth of urban growth and urban sprawl. The urban modelling, extension of urban land, growth and sprawl can be understood by machine learning algorithms.

LULC has been associated with the physical and spatial characteristics of urban landscapes, which are commonly used to identify urban sprawl and spatial dispersion. With increased availability of satellite RS data and rapid development of GIS and landscape ecology approaches, many studies have been conducted to quantify urban expansion in various cities around the world (Seto et al., 2011; Solon, 2009) The landscape metrics can be computed and analysed from the thematic maps derived from aerial or satellite images. GIS related software tools have primarily been used to predict the expansion of LULC. In this paper, the accuracy of prediction can be enhanced by using R programming. In this way, detection can be more precise and accurate. In this study, we aim to compute and detect LULC changes from 1997 to 2017 and examine the temporal and spatial growth patterns and the urban situation more accurately.

2 Study area

Thoothukudi is a district of the Indian state of Tamil Nadu, it is also called a port city, and the gateway to south Tamil Nadu by the coast. It lies in the coast of the Bay of Bengal. The geographical location of the city of Thoothukudi lies between 8.81° N and 78.14° E with an elevation between 4 m above the mean sea level. Thoothukudi is also identified as Pearl City due to its role as a major centre of pearl fishing over several centuries. The city is significantly urbanised, industrialised and occupied with salt pans.

According to the 2011 census, the city has a population of about 410,760. The major community of the people are employed in fishing, trading, salt pans, industries and tourism. There are 21 islands situated between Thoothukudi and Rameswaram shores (Gulf of Mannar), so the area is identified as a Marine Biosphere Reserve of India. Thoothukudi is one of the major business hubs of India, including sea-borne trading, thermal power plant and Sterlite copper industries, with an unparalleled expansion of urban sprawl and infrastructures.

Thoothukudi has been one of the fastest-developing cities in Tamil Nadu over the last four decades. The rapid urbanisation and industrialisation has resulted in uncontrolled urban sprawl, which drives air and water pollution, encroachment, discharging of water into coastal areas and unregulated clearance of waste.

3 Data used

Three decades of Landsat TM satellite images with 30 m resolution, remotely sensed from 1997, 2007 and 2017, were used (Table 1). These Landsat thematic mapper data were attained from the US Geological Survey (USGS) portal. World Geodetic System (WGS) 1984 was used for projection.

Table 1 Data description

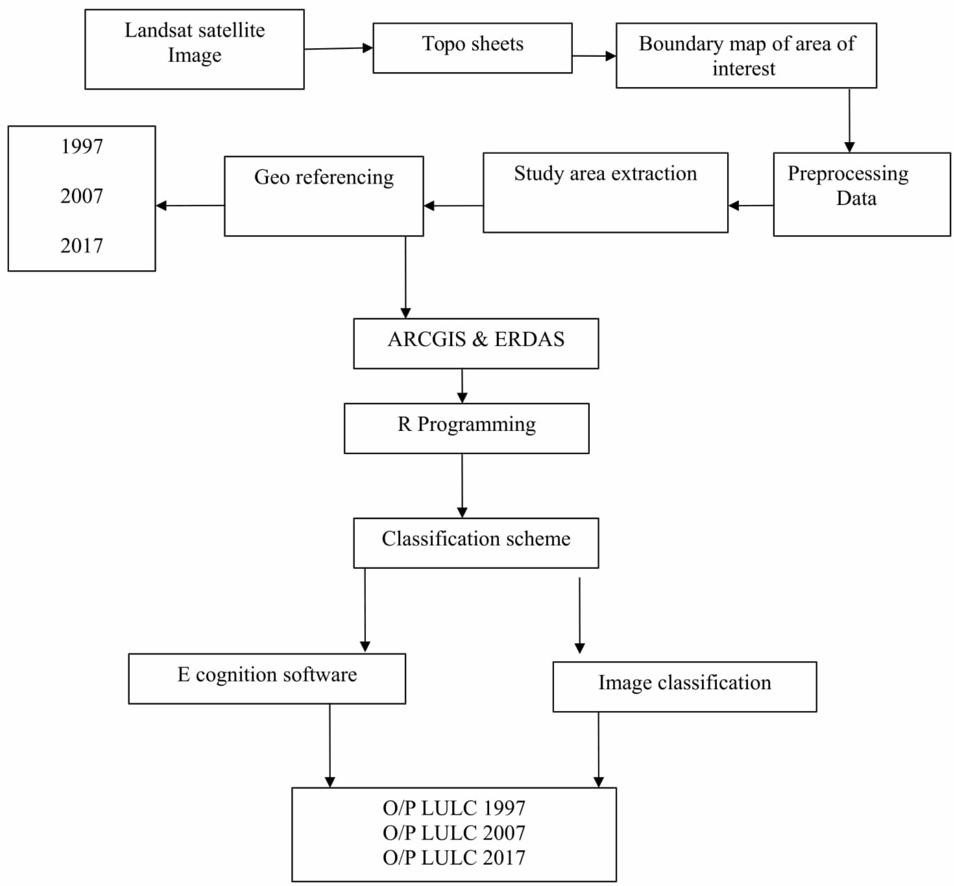
Date	*Sensor*	*Path/Row*	*Format*
August 25th, 1997	Landsat-5	142/51	GeoTIFF
May 9th, 2007	Landsat-7	142/51	GeoTIFF
July 4th, 2017	Landsat-7	142/51	GeoTIFF

4 Methodology

4.1 Satellite image pre-processing and land use and land cover mapping

The available multi-temporal data obtained from the remote sensing techniques helps to study the supportive patterns and developments of changes. The LULC is mainly significant for environmental studies, urban dynamics, urban sprawl model and sustainable development. Therefore, updated terrain classification is always a prerequisite for urban sprawl studies. Figure 1 shows the flow chart for image pre-processing and classification and result validation.

Figure 1 Methodology for image classification and result validation



4.1.1 Image pre-processing

The different set of Landsat Enhanced Thematic Mapper (ETM) data was initially geo-corrected and rectified. The whole scene size of satellite imagery of ETM data was cropped to the study area. The spatial resolution of the ETM data of different time periods from different sensors has a variant spatial resolution. In order to maintain uniformity in spatial resolution, the ETM data was re-sampled. The study area includes the Thoothukudi city administrative area and a 10 km buffer from the city boundary. The final subset imagery of study area was obtained from Earth Resources Development Assessment System (ERDAS) Imagine for further classification.

4.1.2 Image classification in R programming

Object-based classification in R programming is becoming more advantageous for classifying high-resolution satellite images at the object level instead of the pixel level. R programming is a software environment for statistical analysis, graphics and representation. Relevant features of R programming include that it is well developed and uses simple language. It has an effective data handling and storage facility. It provides a suit of operators for calculation, arrays, lists, vectors and matrices. Considering the above features, R programming has been chosen for the study. Random forest (RF) classification is one of the machine learning algorithms increasing in concern for object-based classification because it produces automatic, accurate results and has a non-parametric nature compared to other conventional classification methods. We used an RF package in R for LULC classification.

4.1.2.1 Land classification schema

The study extracted seven land use classes from the resultant image classification. As far as the city of Thoothukudi is concerned, it is a fast-growing city in the state of Tamil Nadu which consists of several industries, including a thermal power plant, chemical plants, a harbour and seafood export companies. Due to the development and increase in industrial growth, several land use parameters change day by day. Hence, an accurate estimation of these changes in land use parameter becomes essential to predict the growth of the city.

The categories and its corresponding classes are explained in Table 2. These are the prime factors influencing the LULC changes in the study area.

Table 2 Land use and land cover nomenclature

No	*LULC classes*	*Land uses included in the class*
1	Water bodies	Rivers, streams, open water and ponds
2	Built-up land	Residential, Industries, roads, airport and other related built-up areas
3	Agriculture	Agricultures and grazing area
4	Bare land	Dry land, ready for construction and real estate plots
5	Fallow land	Non-irrigated lands
6	Salt pan	Salt water pool constructed for water evaporation process
7	Shrubs	Bush and woody plants

- Water bodies

  Water bodies are the most significant part of the landscape, which includes rivers, ponds, lakes, etc., as they supply water, recreation and suitable places to live for several inhabitants. Due the increase in population and industries, these water bodies are reduced to a great extent, which drastically affect the living inhabitants. The type and severity of reduction in water bodies can be estimated precisely to estimate the LULC changes. The analysis of water bodies in LULC is taken as a key factor in studying and assessing the LULC.

- Built-up land

  Land use pattern changes due to the increase in economy of people. As a result of economical growth, land is being used by people for purposes other than agriculture. Primarily agricultural land is used for building purposes, particularly around the urban area. The development of the city in terms of built up land significantly affects the agricultural land and the cultivation of vegetables, food, etc. Hence estimation of built up land is a prime influencing factor in LULC.

- Agriculture

  Land is a natural resource for the agricultural sector, and the use of land for agriculture purposes plays a vital role in the survival of human life. Economic and industrial development of the city affects agriculture and has a greater impact on the development of the country, so it can be used to assess the development of LULC.

- Bare land

  Bare land is nothing but vacant land suffering from a lack of soil and water facilities. With recent technology, bare land is converted into agricultural land by providing vegetative cover. With the increase in population, huge acres of agricultural land are needed for food production. Hence estimation of bare land is essential to bring vegetative cover by adopting recent technology.

- Fallow land

  Due to the rapid increase in population, it is very difficult to control development activities on fallow land. The expansion of land use is influenced by technological development. Technological inventions motivated intense cultivation, which makes the conversion of fallow land into productive agriculture land. Hence prediction in the change of fallow land is essential for LULC.

- Salt pans

  Salt is the major ingredient that produces taste in food items. Production of salt involves a large investment and considerable labour. Thoothukudi is well known for salt and is called the salt city of Tamil Nadu, because it produces a large quantity of salt. Producing a large quantity of salt requires large units of salt pans. Increases in salt pans reduce the amount of agricultural land and water bodies. Hence it is a key parameter for LULC.

- Shrubs

  Human livelihood depends on agriculture. Farmers expand their farms to increase food production and hence destroy shrubs/forest for their farm expansion and for fuel. The destruction of forest and shrubs changes the ecosystem and subsequently the sources of animal feed and natural energy. Estimation and analysis of shrubs is considered a key factor in LULC.

4.1.2.2 Image segmentation

The spatially and spatially-cohesive features on the ground are divided by running segmentation algorithms in the ENVI feature extraction tool. This segmentation process is used to locate several regions with maximum homogeneity. The features in the region can be vegetation covers with parallel structure, appearance, and colour. The segmentation algorithm reduced the heterogeneity of image features or objects for a given resolution. The segmentation image from classified raster data is obtained by providing minimum and maximum threshold value of pixels and population of pixels that are essential in a selective region.

4.1.2.3 Computation of zonal statistics

The values of raster output from image segmentation are summarised within the zones of boundaries map data set; thus, it manages to decrease the irregularity in the image. In segmentation data with very high resolution and segmentation, the area outside the image boundary is all characterised in the pixels. By computing the zonal mean for a complete region, this unevenness is reduced.

4.1.2.4 Zonal analysis

To understand urban growth in Thoothukudi, the city boundary with 10 km buffer region is mapped. The study area covers the neighbourhood district region and is divided into four geographic zones: Southeast (SE), Southwest (SW), Northwest (NW) and Northeast (NE). Urban growth is studied in the different zones in order to estimate urban sprawl in Thoothukudi over different periods.

4.1.3 Accuracy assessment

Accuracy assessment is used to evaluate the performance of classification and ensure the predictions are suitable. This study followed kappa coefficients to analyse the accuracy of three decades of classified images. The producer data was obtained from field surveys and Google Maps; user and producer accuracies were calculated through a confusion matrix. The kappa coefficient index was calculated for three different dates of land use classified images in eCognition Developer. In order to maintain high accuracy, the number of the sample size (n) is obtained from the equation.

5 Results and discussion

To analyse LULC change and its impact on a harbour city, Thoothukudi was chosen as a study area, and data were collected around the city. To investigate the expansion of LULC, Landsat Enhanced Thematic Mapper (ETM) data images were taken as sample images. Images for the period of 1997, 2007 and 2017 were taken as test sample images. The major objective is to enhance the accuracy of classification. This can be done by adopting R programming before the classification stage.

5.1 Land use and land cover classification and accuracy assessment

Random forest classification in R programming is applied to produce LULC map of the study area for different time periods are shown in Figures 2, 3 and 4. The accuracy of derived map is examined in eCognition software with training samples which are collected from google maps and ground truth. The overall accuracy for the LULC map of 1997, 2007 and 2017 are 0.92, 0.97 and 0.92 respectively, it shows the accuracy value were above the satisfactory level. Thus, the classified map and ground truth samples are closely associated to be used for further analysis and modelling. The accuracy assessment value of several classes with different corresponding years is given in Table 3.

Table 3 Summary of confusion matrix for the classified images 1997, 2007 and 2017

Classes	*1997*		*2007*		*2017*	
	Producer accuracy	*User accuracy*	*Producer accuracy*	*User accuracy*	*Producer accuracy*	*User accuracy*
Waterbodies	91.05	92.32	82.02	98.09	78.12	80.25
Built-up land	98.45	93.58	93.04	97.12	84.56	82.78
Agriculture	96.68	91.56	98.56	86.45	96.04	97.31
Bare land	93.65	92.05	84.51	89.47	92.78	92.23
Fallow land	92.01	92.02	94.03	88.12	76.05	95.77
Salt pan	93.21	90.12	93.07	97.13	96.44	95.34
Shrubs	89.32	90.22	85.08	96.45	92.45	92.44
Overall accuracy	92	91	97	93	92	90
Kappa	0.92	-	0.97	-	0.92	-

Figure 2 1997 LULC map and graph of the study periods (see online version for colours)

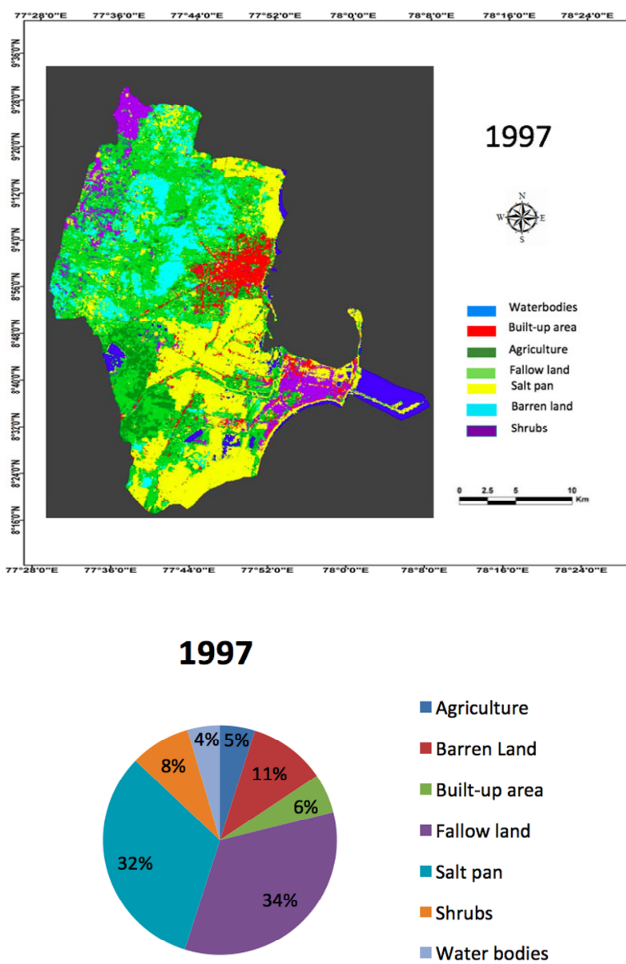
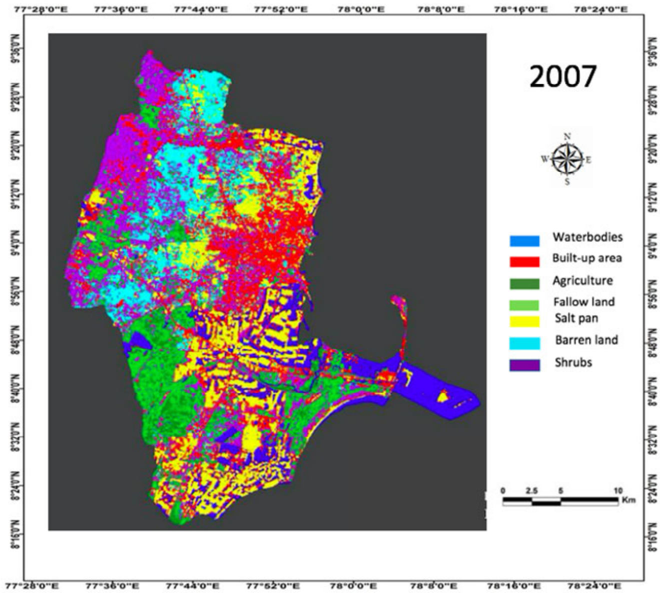
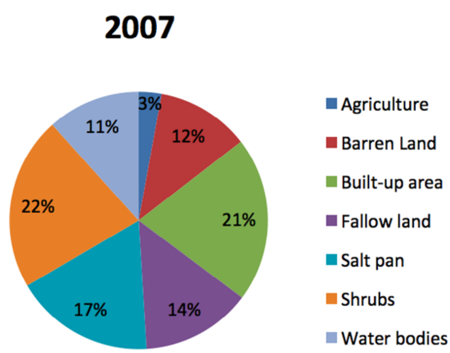


Figure 3 2007 LULC map and graph of the study periods (see online version for colours)

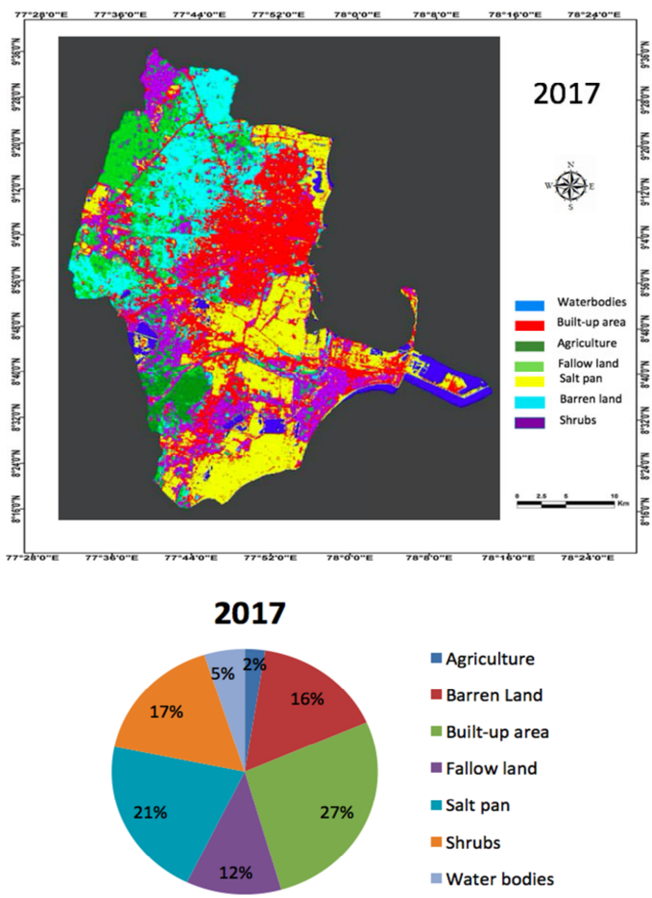




The accuracy for the classification for three decades is given for different classes, especially for water bodies, where the producer accuracy obtained is around 91%, whereas user accuracy value is 92%. Similarly, it is around 82% and 98% respectively for the year 2007, and around 78% and 80% respectively for the year 2017. As far as the build up land classification is concerned, producer accuracy is around 98%, 93% and 84% respectively for the years 1997, 2007 and 2017. Similarly, user accuracy is around 93%, 97% and 82% respectively for the years 1997, 2007 and 2017. Considering the agricultural land expansion, the accuracy is measured similarly to the previous parameters, with producer accuracy around 96%, 98% and 96% respectively for the years 1997, 2007 and 2017, while the user accuracy value lies in the range 91%, 86% and 97% respectively. Bare land accuracies are in the range of 93%, 84% and 92% respectively in the case of producer accuracy for the years 1997, 2007 and 2017 respectively, whereas user accuracies fall in the range of 92%, 89% and 92% respectively. The foremost parameter for the assessment of expansion of LULC in Thoothukudi city is salt pans:

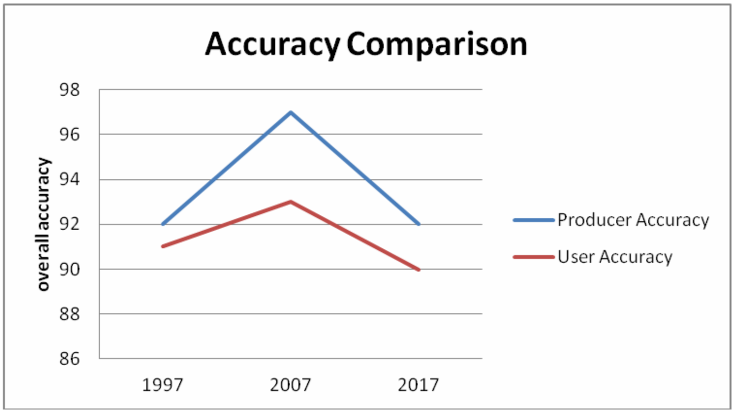
their producer accuracy lies in the range of around 93%, 93% and 96% in the years 1997, 2007 and 2017 respectively. At the same time, its user accuracy is around 90%, 97% and 95% respectively. The same kind of accuracy performance is obtained for the class Fallow land and Shrubs. Figure 5 shows the overall accuracy comparison performance of the expansion of Thoothukudi city using LULC for various years. From the graph, it is evident that prediction accuracy is greatly enhanced by using the R programming concept before classification. The obtained results show that the overall producer accuracy value is in the range of 92%, 97% and 92% for the years 1997, 2007 and 2017 respectively. Similarly, the overall user accuracy is in the range of 91%, 93% and 90% respectively for the same years.

Figure 4 2017 LULC map and graph of the study periods (see online version for colours)



The important assessment parameter for the accuracy is the kappa coefficient, a statistical measure inter-rater agreement for qualitative calculation. If the value of the kappa coefficient is closure to 0.81 to 1.00, it indicates that the accuracy is very high and acceptable. For the three different decades of year examined here, the kappa coefficient value closure to one is obtained and is around 0.92, 0.97 and 0.92 respectively for the years 1997, 2007 and 2017.

Figure 5 Accuracy comparison (see online version for colours)



Most researchers are focused only on analysing or investigating either the quality of water in Thoothukudi city or the impact of the intrusion of sea water on the quality of drinking water resources, since Thoothukudi is one of the fastest growing industrial cities in Tamil Nadu and is situated near the sea shore of the Gulf of Mannar. Hence, analysis and estimation of LULC changes is essential and should be more precise and accurate. The obtained results show that the classification of LULC is more accurate and precise when using R programming concepts.

5.2 LULC identification, analysis and computation

In order to demonstrate the changes in land and the growth of the city, the different classes quantified from LULC maps are shown in Table 4. The examination results show the extensive amount of change in the city and its neighbourhoods.

The transformation of land over the last three decades enormously influences in vegetation land. Between 1997 and 2017, the amount of built-up land has increased more than threefold that is, settlement area has increased by 42.43%. It is possible that this changeover happened in several land areas because the quantification evidently proves the agriculture and shrub land has decreased by 3.861 ha and 26.325 ha respectively. Bare land also increased around 25%; nearly 40% of agriculture and shrub land has been destroyed. The amount of water bodies increased about 11% in 2007, compared with water bodies in 1997 and 2017, but decreased about 5% in 2017. Salt pans are around 32% in 1997 and grow exponentially to 17% and 21% respectively by the years 2007 and 2017. The reason for the increase in salt pans is that Thoothukudi is nearer to the seashore, and the increase in demand for salt throughout the country attracts people towards the production of salt as a profession. India is an agricultural country; most people work in agriculture in order to meet the food demands of the country. But over the last few decades, the agricultural work has become less appealing to people because it requires work throughout the year. Due to climate change, poor rainfall and hot weather, the yields obtained by farmers are not up to satisfaction level. Hence most of the farmers have shifted towards cities and changed to white-collar professions.

In Table 4, it is clearly shown that in 1997, 7.5 ha (about 5%) of the area have been utilised for agricultural purposes, but it is gradually decreased to 3% in 2007 and 2% in 2017. Barren land has drastically increased for the last few decades. Table 4 shows that in

1997 the barren land is around 11%, and it increased to 12% in 2007 and 16% in 2017. It also shows that the reason for the increase in barren land is the reduction of agricultural land for the aforementioned period. This may be due to climate change, poor weather and the loss of farmers to white-collar jobs. Most farmers are uneducated and not aware of recent technology that will allow them to grow their crops in such a way as to yield in plenty. By educating them in the necessary skills and technology, they can be motivated to convert their barren land and fallow land into land suitable for agriculture. As all people need food to survive, every engineering professional should be trained to develop new technology for the former to grow their crops in any environment. The analysis and computation clearly show the growth of built-up/settlements leads to changes in different land use that is, an area of agriculture, vegetation, water bodies and bare land has enormous potential for transformation.

Table 4 Land use and land cover in percentage and hectare during the three-study period

Land class	*1997*		*2007*		*2017*	
	Area (%)	*Area (ha)*	*Area (%)*	*Area (ha)*	*Area (%)*	*Area (ha)*
Agriculture	5	7.592	3	4.463	2	3.861
Barren land	11	16.744	12	18.203	16	25.000
Built-up area	6	8.638	21	32.328	27	42.433
Fallow land	34	52.838	14	21.528	12	18.118
Salt pan	32	50.508	17	27.353	21	33.000
Shrubs	8	13.081	22	34.000	17	26.325
Water bodies	4	7.000	11	18.190	5	7.707
Total	100	156.40	100	156.40	100	156.40

From the results and analysis, it is clear that the following measures should be taken to enhance the environment. Proper control measures should be taken by officials to reduce encroachment on natural resources like water bodies, agricultural land, etc. The development of residential area is not in a radial pattern or concentrated towards places where resources are available in plenty. The town planning authority should ensure a development pattern that will improve the city's development. Farmers and industrialists should be encouraged and motivated to conserve resources through proper awareness programmes. A major cause for the destruction of natural resources is the lack of clear property rights on forest and grassland, resulting in exploitation and misuse of these lands. Because of this lack of awareness, many people think that waste lands are nothing useful and are the symbol of evil spirits. Technological awareness should be created among the people to change their unused land into agricultural land by adopting recent technological innovations.

6 Conclusions

The purpose of computing urban models for a period of time is to understand the growth of the area and regulate land transformation, sustainability and development. The application of geographic information systems, remote sensing, and geospatial modelling tools were assessed used to model urban land use, land cover change and urban growth.

LULC maps of the Thoothukudi area for the years 1997, 2007 and 2017 were obtained using Random Forest classification in R programming, and the computed maps delivered the new development of spatio-temporal distribution of landscapes in the study region. The various environmental factors include fragmented urban growth in outskirts, transformation of vegetation cover and agriculture land into settlements, dense urbanisation in the city region, challenges in sustainable urban planning and suitable land resource provision were quantified and analysed using urban sprawl measurements and landscape metrics. The outcome of the study indicates Thoothukudi city growth highly affected the landscapes, loss of valuable urban vegetation and agriculture land and outward sprawling. Between 1997 and 2007, 14% of agriculture and 10% of shrubs were urbanised/built-up, and 20% of agriculture land was lost between 2007 and 2017, while 25% of bare land became urban settlements between 1997 and 2007. The absence of involvement in agriculture, urban clumpiness in the city centre and increasing population are the main reasons for such massive land transformation. The computation and modelling of urban growth patterns emphasise the essential for well-judged land use distribution and transformation, as well as the preparation of urban development policy with an emphasis on the sustainable deployment of natural resources. Land allocation strategy should follow the land availability and capability classification of Thoothukudi city to achieve sustainable urban expansion and development.

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