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Abstract
Land is a major natural resource needed for infrastructure development, economic activity, and human livelihood. Dynamic interactions between humans and the environment led to dynamic changes in land use patterns over time. Agricultural lands are threatened by urban expansion and environmental pressures, resulting in reduced food production, biodiversity loss, and habitat degradation. Therefore, understanding the dynamics of agricultural land use is vital for planners and policymakers. This study examines Melur Taluk in Madurai district, Tamil Nadu, India, which serves as a representative case of rural transformation in India. A 30-meter spatial resolution, multispectral bands, and 12-bit radiometric resolution Landsat image was utilized to process the data. The research employed a maximum likelihood classifier (MLC) to study the main causes of agricultural land use change between 2011 and 2022. The artificial neural network (ANN) time series framework was used to study previous and future trends by evaluating historical data and forecasting patterns in socio-economic and other physical and environmental variables. This integrated ANN based modelling approach supports data driven decision making and is used for better interpretation of land transformation patterns in land use planning.

Key words: Agricultural land use change, remote sensing, artificial neural networks, Melur Taluk, land cover prediction.

Introduction
The land is highly dynamic in nature, and it is influenced by both natural and manmade sources (Değermenci, 2023). Indian agriculture is both a requirement for economic development and a problem for economic development that reduces poverty. India's dependence on agriculture is

determined by the massive pressure population growth places on the country's land, water, biodiversity, and other natural resources (Prabhakar, 2021). Securing food supplies, increasing export revenue, and promoting dispersed development are all critical to reducing rural poverty (Ain *et al*., 2025; Urugo *et al*., 2024; Nontu *et al*., 2024). The basis for agricultural production is land utilization. Historically, soils and water resources have always been responsible for sustaining life support systems and the main source of income for most people on Earth (Saif-Ud-Din *et al*., 2022). Effective management and use of land resources are essential to ensure human wellbeing and socio-economic development.

Melur taluk in Madurai district, Tamil Nadu, a typical non-metro area in India, was selected as the area of study, which has undergone significant changes in land use. To fulfil the demands of its increasing population, it must import a large amount of food items from external sources. This productive land area is also greatly impacted by infrastructure improvements (Hoose and Kripka, 2021). These changes are an indicator of the increasing pressure on the local resources and a sign of the need to plan land use. This is one of the most manageable problems that need attention in order to appropriately plan for the long-term sustainability of these priceless resources. In order to address this predicament and assist the area in becoming self-sufficient, it is crucial to study the variables influencing the pattern of land usage. An investigation of this type is useful in developing policies and plans to improve the effectiveness and efficiency of our scarce resources. In order to forecast changes in agricultural land specific to the study location, an appropriate model with a minimal number of input parameters has been developed in this research effort. Recent studies confirm the growing importance of socio-economic variables in the determination of land use and land cover (LULC) change patterns. For example, Yang *et al*. (2023) adopted shared socio-economic pathways within a cellular automata (CA)-Markov framework for urban expansion modelling along coastal zones. The results demonstrate the role of socio-economic variables in preventing non-sustainable growth. Likewise, Chuma *et al*. (2022) compared the influence of income requirements, land use attitudes, and household demographics on wetland conversion in the Democratic Republic of Congo (DRC)'s South-Kivu. Forkuo *et al*. (2021) proved that population movement, land ownership systems, and economic stress were the leading factors behind Ghana's Ashanti region LULC change. The works highlight the importance of incorporating socio-economic aspects into predictive models of LULC.

The remote sensing (RS) and artificial neural network (ANN) are valuable for LULC change detection, LULC analysis, and prediction in studies across regions. Abebe *et al*. (2022) investigated the LULC changes in Northeast Ethiopia during the previous 30 years using RS. The analysis revealed a 9% increase in settlement and agricultural land and an expansion of bare and scrubland. Grazing land decreased from 11.1% in 1986 to 5.7% in 2016, and forest decreased from 8.9% to 2%. The study also pointed out the main factors behind these changes, which include lack of public awareness, climate change, and population growth. Zhu *et al.* (2022) proposed using the Siamese global learning (Siam-GL) model to detect the change in high spatial resolution (HSR) RS imagery, which extracts features from a pair of bi-temporal images efficiently. Unlike the existing systems, Siam-GL first integrates deep learning (DL) with the shared parameter of the Siamese architecture. The findings suggested that Siam-GL outperformed the other methods in generalizing with large datasets. In this work, Lv *et al.* (2022) introduced a neural network to detect land cover changes based on RS images with the aid of multi-scale dilation convolution modules and spatial spectral attention techniques. The results showed that the offered method outperformed five methods by attaining an enhancement of 0.08–14.87% in overall accuracy (OA) for Dataset-A.

Das and Angadi (2022) evaluated LULC changes in the Barrackpore subdivision of India using the MLC method and multi-temporal Landsat images. The analysis showed LULC changes from 1972 to 2016: water bodies decreased by 1.7%, wetlands decreased by 6%, agricultural land decreased by 7%, vegetation decreased by 23%, and wasteland and built-up areas increased by 6.3% and 32.2%, respectively. Li *et al.* (2022) developed a multi-scale fully convolutional network (MSFCN) with a global pooling module (GPM), channel attention block (CAB), and various scales convolutions to obtain useful information from 2D satellite images. The MSFCN was extended to 3D by using a 3D convolutional neural network (CNN) to obtain spatio-temporal relationships in RS data. The findings indicated that MSFCN achieved mIoU of 75.127% on the Gaofen image dataset (GID), 60.366% on the Wuhan dense labeling dataset (WHDLD) dataset, and 77.156% and 87.753% on spatio-temporal datasets.

Girma *et al.* (2022) identified LULC changes from 1985 to 2050 in the Gidabo River basin under business-as-usual conditions using various spatial datasets like Landsat images of 1985, 2003, and 2021. The study used an integrated image classification method to examine past land use trends, and future LULC projections for 2035 and 2050 were made using the CA-Markov chain and multi-layer perceptron neural network (MLP-NN) models in Tercet software. The results showed that water bodies, settlements, and agricultural land increased while grasslands, shrubs, and forests declined. Jaleyer *et al.* (2022) analyzed the LULC changes in the Chalus watershed in 2001, 2014, and 2021 using multitemporal Landsat images. The study employed pixel- and segment-based hybrid classification approaches to generate maps of LULC. For change probability maps, the study used a support vector machine (SVM) algorithm and a Markov chain model for change probability matrices to predict LULC changes for 2021 and 2040. The result revealed a decrease in forest and grasslands and an increase in barren lands and agricultural lands. The model predicts a further loss of forest cover and expansion of built-up areas, agricultural land, and wasteland by 2040.

Foley *et al*. (2005) have opined that land use change, whether it is through altering management techniques in human-dominated landscapes or transforming natural landscapes for human uses, has emerged as the main force behind change in the earth system. In this research, Landsat 7 image has been used with a spatial resolution of 30 meters, 8-bit radiometric resolution, normalized difference vegetation index (NDVI) and soil adjusted vegetation index (SAVI) were used as vegetation indices. According to Wang *et al.* (2022), when studying changes in LULC, it is necessary to define the spatial and temporal scales of analysis. This process i) guides the selection of the specific land cover and use categories to be analyzed; ii) influences the identification of driving forces such as NDVI, enhanced vegetation index (EVI), rainfall, and processes responsible for these changes; iii) influences how the connections between LU and LC are identified and explained within specific spatiotemporal frames. Yan *et al.* (2009) contend that the environment, ecosystem services, and agricultural food production are all significantly impacted by LULC changes, such as those in agricultural methods, urban expansion, and deforestation. Parameters such as climate, NDVI and SAVI used in this study are important to understand the effects of LULC changes, address them, improve management of accessible resources, and develop appropriate land management strategies.

Baig *et al.* (2022) assessed LULC changes and predicted future trends from 1991 to 2021 in Selangor using satellite imagery. LULC maps were created for SVM classification in ArcGIS. The cellular automata (CA)-ANN technique predicted LULC changes from 2031 to 2051 with 82.43% accuracy and a kappa value of 0.72. Saha *et al.* (2022) studied the LULC changes in the Himalayan foothills from 1991 to 2021 and predicted the changes up to 2050 using supervised classification with the MLC tool on Landsat images. The findings showed a decline in fallow land, agricultural land, and vegetation land while plantation and built-up areas increased. The prediction results indicated that by 2050, 12% of the region will be covered by built-up areas, and agricultural land will decrease to 24%. Panda *et al*. (2024) developed a LULC prediction model integrating a hybrid predictive screening practice CMD with CA-ANN.

The model trained using LULC maps from 1995 and 2005 and tested with 2020 maps found that CMD predictors were effective, followed by Decision Tree variables. The model predicted changes by 2080 showed an increase in built-up land, cropland, shrubland, and water bodies, while forest and wasteland were expected to decrease. Kafy *et al*. (2021) studied the impact of LULC changes on land surface temperature (LST) in Dhaka from 2000 to 2020 using Landsat images. The study used the SVM algorithm for LULC classification and used cellular automata and ANN algorithms to forecast future LST and LULC changes for 2030. Over the last 20 years, there has been a 7.24°C increase in LST, accompanied by a 14% increase in built-up areas and a 5% decrease in plant cover. According to the study, by 2030, the LST is predicted to increase by 9.29°C due to a 13% decrease in urban green cover and a 21% increase in built-up areas. In addition, socio-economic variables like land tenure regimes, domestic income, and financial incentives are being recognized to a greater extent in driving LULC. System Dynamics and Plus models were used by Tian *et al*. (2025) to show how socio-economic factors and climatic conditions affect habitat quality in the Poyang Lake Basin. Analogously, Wubetie *et al*. (2025) used the DPSIR framework to ascertain how variables such as landholding size, household size, and market proximity affect land conversion in rural Ethiopia. Such findings highlight the necessity to incorporate human dimensions into LULC change evaluation and emphasize that socio-economic variables are not peripheral but essential in landscape changes.

The observations made from the literature review are summarized. More precise classification is needed for both high- and low-resolution satellite images. New classifiers are needed to enhance the classification accuracy, as the MLC classifier is discovered to be extensively employed in image classification according to the literature. Changes in climate and social class represent significant challenges for agricultural development. Without considering the underlying factors that drive LULC change, the effects of these changes cannot be thoroughly comprehended. Identification of the changes in land use driver involves analyzing both the frequency of these changes and their spatial and temporal dimensions. It also requires examining alterations in both the amount and quality of land use over time. Indices such as NDVI, EVI, and SAVI are generally used in the literature to identify vegetation. The observations commonly found in literature reviews on ANNs include the rise of machine learning, a subset of ANN involving deeper networks with multiple layers, which has significantly improved performance, and ANN models, particularly Feed forward networks with backpropagation and recurrent neural networks, have outperformed machine learning models in several benchmarks. To assess LULC patterns, the multi-layer perceptron (MLP) model was trained using various influencing factors, which helped in producing predictive maps. The application of both ANN and MLP models demonstrated their effectiveness in analyzing and forecasting LULC changes across multiple geographic areas. The results imply that artificial intelligence can increase classification accuracy and make better predictions of LULC in the future.

The novelty of this study lies in its integrated approach to analyzing agricultural land use dynamics in Melur taluk, Tamil Nadu. It combines RS techniques with ANN to predict future land use changes by considering physical, environmental, and socio-economic factors. When compared to previous studies, this study focuses on the Melur taluk region with less existing research and uses decade-old Landsat imagery with ground truth validation. The prediction of future trends (2033 and 2044) using Markov chain analysis and ANN modeling provides an understanding of sustainable agricultural and urban land management. The primary objective of this study is as follows;

- To prepare LULC maps for the study area using the Landsat image and perform change detection analysis for the years 2011 to 2022.
- The goal is to identify the relationship between physical, socio-economic, and environmental factors that influence the dynamics of agricultural land use using collateral data sets.
- To develop, calibrate, and validate the ANN model for predicting agricultural land use.

Data collection and methodology

Proposed methodology

The methodology used in this study involves the following steps. Landsat 7 and 8 imagery of the study area is used for analysis, allowing for the identification of various agricultural features, settlements, and water bodies. Spectral classification of the imagery was carried out using the MLC method to develop LULC maps and detect changes in agricultural patterns. Key drivers for modelling were identified using various literature and ANN techniques. The model results obtained through ANN are compared and validated against actual and predicted LULC maps. A flowchart showing the methodology is given in Figure 1.

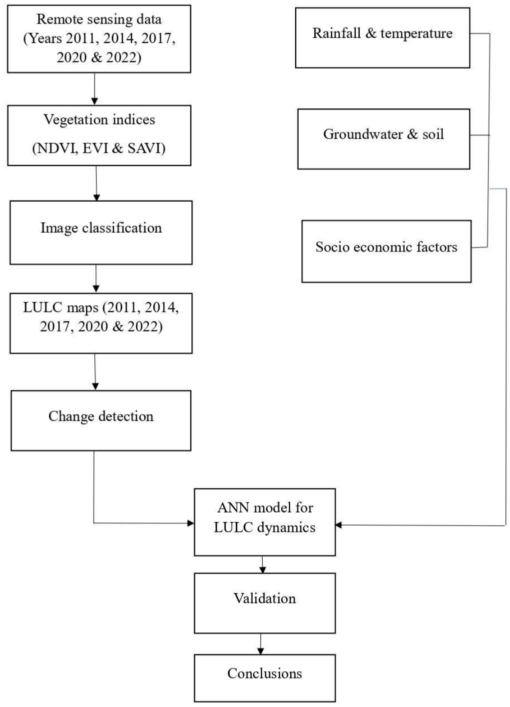

Figure 1. Flowchart of the methodology used.

Description of study area

Melur taluk in Madurai district, Tamil Nadu, India, is the study area that has been chosen for this paper. The study area is approximately 681 square kilometers. It is situated between 10° 1′ 50″ north latitude and 78° 20′ 24″ east longitude. It is bordered by the Dindigul district to the north, Sivagangai district to the east, Theni district to the west, and Virudhunagar district to the south. Due to its agricultural productivity, the area under study is commonly known as the "granary" of the district. Fertile land, one of the study area's most valuable yet limited resources, is being increasingly impacted by non-agricultural activities, leading to a reduction in available fertile land. This significant decrease in reported agricultural area underscores the necessity of conducting a comprehensive land use study using RS and ANN techniques.

Software and data used

ArcGIS is a geospatial application intended for the visualization, modification, management, and analysis of geographic data. ArcGIS software has been used in this thesis for image classification and LULC map preparations. With specialized libraries and toolkits, like the Mapping Toolbox, MATLAB software has been used in this research for ANN modelling of the changes and trends in the way agricultural land is utilized over time. The data used as the input used for ANN modelling are rainfall, temperature, soil, groundwater, socio economic data, indices, and target LULC data were used.

Preparation of LULC map and change detection

The LULC maps are prepared for the years 2011, 2014, 2017, 2020 and 2022. The LULC map for the year 2022 is prepared to serve as a primary reference (used for ground truth verification). The image classification includes categories such as settlement areas, forests, vegetation (agriculture), and water bodies. Additionally, agricultural land is further categorized into plantations, fallow land, and cropland, while wasteland is also included in the mapping process. In geographic information systems (GIS), overlaying polygons is a common approach, as it incorporates spatial data that aids in tracking changes in LULC. This method offers more detailed insights into the initial and final land cover types. The spatial distribution of changes is represented on a land use change map, highlighting the shifts that occurred over these time frames.

LULC change model

The development of the ANN model has demonstrated significant potential in overcoming various challenges in change detection using RS. Representation learning is the main component of Machine learning based on ANNs. Models in Machine learning provide better power and flexibility by demonstrating complicated ideas as layered hierarchies. Within this structure, every idea is determined by easier ones so that more abstract representations can be formulated from less abstract bases (Montesinos López *et al*., 2022; Zhong *et al*., 2022).

Preparation of drivers

The drivers used in this study are shown in Table 1. The preparation of data, often known as the "drivers" of an ANN, is an extremely crucial step that significantly affects the performance of the model. This procedure begins with a high-quality dataset relevant to the task. Before data preparation and polishing can take place, data collecting must take place. Thus, it involves handling missing data, addressing outliers, and removing inconsistencies to ensure the reliability of the dataset.

A combination of physical, environmental, and socio-economic factors was used to determine the strongest drivers of the ANN model due to a literature review, domain relevance, and statistics. Important variables like annual rainfall, maximum temperature, minimum temperature, groundwater level, soil, population, literacy rate, sex ratio, work participant rate, non-working population rate, NDVI, EVI, and SAVI were taken into account. The regression analysis was done to assess the level of these variables and the transition in land use. It is based on this that the most representative drivers that control the dynamics of agricultural land in Melur taluk could be selected.

Table 1. Drivers used in this study.

Major driver	Type	Sub driver
Physical and environmental drivers	Climate	Annual rainfall
		Maximum temperature
		Minimum temperature
	Terrain	Groundwater level
		Soil
Socio economic drivers	Class	Population
		Literacy rate
		Sex ratio
		Work participant rate
		Non-working population rate
Indices used	Vegetation	NDVI
		EVI
		SAVI

Results and discussion

Trend of rainfall

This study takes climate records from 2011 to 2022 to analyze past climate trends and the ANN model to predict future trends. In 12 years, rainfall patterns changed with 7 years of normal rainfall and 5 years of rainfall above normal. The years 2011, 2014, 2017, 2020, and 2022 have been considered because of their excess rainfall. The collection of data is focused on these years, and rainfall anomalies used for ANN modelling are presented in Table 2. December has been taken into consideration based on the research area's crop calendar since it is the crucial month for mapping and modeling. The hydrological year from June to May has been considered for measuring rainfall because it gives a better idea of the availability of water. Climate studies and agricultural planning are advantageous for this method.

Table 2. Rainfall Anomalies used for ANN modelling.

Year	2011	2014	2017	2020	2022
Anomaly	-1.92	-1.76	1.47	1.49	1.52

Trend of temperature

The temperature is an important driving force for agricultural growth and productivity. Temperature trend mapping of the study area for selected years considers annual means of maximums and minimums during Southwest Monsoon (SWM) and Northeast Monsoon (NEM) seasons. Temperature anomalies for ANN modelling are presented in Table 3. It was noted that the minimum temperature increased at a faster rate compared to maximum temperatures. During SWM and NEM, the mean highest temperature is 29°, and the mean lowest temperature is 21° annually. The SWM accounted for a higher temperature than the NEM. Since the peak crop-growing period for most crops happens during the NEM, increments in temperatures may adversely impact a lot of farmer's crop yields. During SWM, the increase in the highest degree is found to be higher than NEM. The increase in temperature during NEM should, therefore, create an unfavorable impact on the productivity of many annual crops since the main crop-growing season is during NEM.

Table 3. Temperature anomalies used for ANN modelling.

Year	2011	2014	2017	2020	2022
Anomaly	-0.35	0.09	0.09	-0.12	-0.19

Trend of groundwater

Between 2011 and 2022, the study area experienced noticeable changes in groundwater levels and the groundwater anomalies used for ANN modelling in Table 4. These fluctuations are primarily influenced by factors such as variations in rainfall, agricultural practices, urbanization, and land-use patterns. During the early part of this period, particularly from 2011 to 2014, groundwater levels showed moderate declines due to increased irrigation demand and irregular monsoon patterns. However, during years of adequate rainfall, there are some improvements in the water table. In the mid-decade, around 2015, groundwater levels dropped considerably in many areas. Many initiatives are geared towards addressing the dwindling state of underground water from 2018 to 2022, rainwater harvesting, and simple awareness of sustainable water practices.

Table 4. Groundwater anomalies used for ANN modelling.

Year	2011	2014	2017	2020	2022
Anomaly	1.77	0.31	1.14	-0.783	-0.81

Trend of soil

The soil type in the study area is red loamy soil, characterized by good drainage and moderate fertility. Also, this soil is able to support paddy, pulses, and millets. This soil texture is suitable for the agricultural economy of the region; it gives a strong base for rooting and water absorption. Changes in soil properties occurred in the study area between 2011 and 2022, resulting from both environmental influences and agricultural practices. During this period, the irregular rainfall patterns with drought increasing erosion reduced soil moisture and degradation susceptibility of certain areas. Therefore, those changes are considered for the modelling process.

Trend of NDVI

The NDVI is one of the main components in LULC mapping derived from satellite imageries that measure vegetative health and density of the study area. In this study, NDVI maps were prepared for the years 2011, 2014, 2017, 2020, and 2022. The NDVI built for 2011 and 2022 are represented in Figure 2 a,b. The NDVI ranges from -1 to 1; higher values reflect high and healthy vegetation density, and lower values reflect sparse and stressed vegetative cover or stay as an impervious surface like urban areas or surface water. The maximum value for the study area is +0.59, and the minimum value is -0.6. NDVI anomalies used for ANN modeling are summarized in Table 5. In ANN modeling for LULC, NDVI provides key input because it can be used to quantify and measure conditions in vegetation. The NGDI performs better with certain other parameters, such as topography, soil characteristics, and socio-economic data, which are used to feed the ANN model. The ANN models are used to capture complex interrelations and learn associations among land cover types influenced by environmental or anthropogenically induced factors. Therefore, ANN leads to improving the predictive accuracy of the model.

Table 5. NDVI anomalies used for ANN modelling.

Year	2011	2014	2017	2020	2022
Anomaly	-1.18	0.80	0.45	0.68	0.71

Trend of EVI

The EVI is another key performance indicator for LULC mapping, and it demonstrates its ability to provide vegetation density and health changes. Compared to NDVI and similar indices, EVI is developed to lessen the influence of atmospheric interference, soil reflectance, and cloud cover. The area under the study shows a maximum value of 0.69 and a minimum value of -0.29. The EVI maps for the years 2011, 2014, 2017, 2020, and 2022 were prepared in this study. Figures 2(c) and (d) illustrate the EVI map for 2011 and 2022. In Table 6, the EVI anomalies used in ANN modelling are indicated. The information thus entered as ANN input through EVI accede important information for effective identification and differentiation of forest, agriculture, and urban land cover types. By allowing the ANNs to engage in background learning processes pertaining to the relationships that vegetation changes have with time, EVI further enhances the prediction capability of land cover.

Table 6.EVI anomalies used for ANN modelling.

Year	2011	2014	2017	2020	2022
Anomaly	-1.11	0.82	0.44	0.77	0.68

Trend of SAVI

The SAVI is a modification to the vegetation index aimed at minimizing the effect of soil brightness on plant cover assessment. Also, it is useful in soils that conform to some layers of soils that are unexposed to seasonal cropping patterns associated with typical agricultural management practices. In the study area, the condition of the vegetation cover was moderate due to farming and land-use practices. Table 7 presents the SAVI anomalies used for ANN modeling. For this study, the SAVI map was developed for the years 2011, 2014, 2017, 2020, and 2022. The 2011-2022 SAVI map is illustrated in Figure 2 e,f. By using SAVI, agricultural and environmental researchers were able to obtain a more precise analysis of crop health and land cover changes. This helps with better land management, sustainable farming practices, and improved decision-making for enhanced agricultural productivity.

Table 7. SAVI anomalies used for ANN modelling.

Year	2011	2014	2017	2020	2022
Anomaly	-1.12	0.84	0.51	0.69	0.74

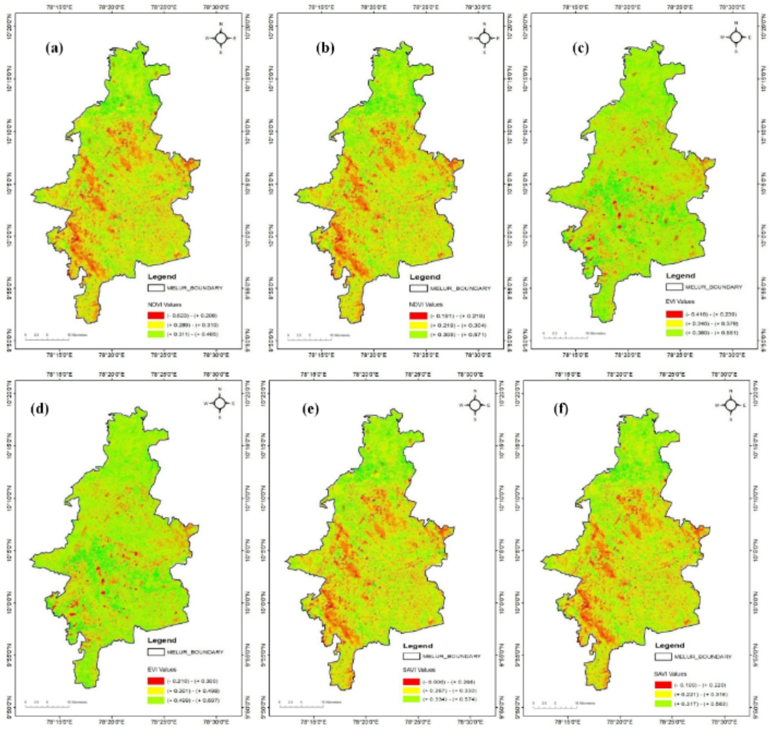

Figure 2. Vegetation indices over time (a) NDVI in 2011, (b) NDVI in 2022, (c) EVI in 2011, (d) EVI in 2022, (e) SAVI in 2011, and (f) SAVI in 2022.

Trend of population growth

Population growth significantly drives land use changes, leading to a reduction in cultivated land and an increase in urbanized areas. The population in the study area experienced notable growth between 2001 and 2011, reflecting significant demographic changes in the region. The population was approximately 2,51,919 in 2001, and by 2011, it had risen to around 2,90,985. This increase of about 78,094 individuals over the ten-year period corresponds to a growth rate of roughly 8.9%. Alongside the rising population, the population density also grew, reaching approximately 670.76 people per km^2 in 2011, compared to 627.76 people per km^2 in 2001.

Trend of literacy rate

In the research region, literacy improvement between 2001 and 2011 reflects the improvements in education in the region. In 2001, literacy was 67.45%, which was an urgent need for improvement. In 2011, the literacy rate rose to 76.64%, which is an improvement of 9.19%. The increased literacy shows commitment to socio-economic improvement in addition to increased access to education.

3.10 Trend of sex ratio

The sex ratio varied from 2001 to 2011. It was an equal ratio in 2001, with 1,029 females for every 1,000 males. The sex ratio by 2011 reduced to 1,008 females for every 1,000 males. This decline is comparable to trends in several parts of India. This result is due to factors such as cultural beliefs, money problems, and population changes that affect the number of males and females. Such changes raise a few other issues relating to gender discrimination, thereby putting forward the imperative to keep going in the direction of gender equality and protection of women's rights in the region.

Trend of working and non-working participation rate

Based on data from the Census of India 2011, the total population of the study area were approximately 290,985 people. Among this, the total workforce is divided into two main categories: main workers and marginal workers. Out of the total working population, there are 116,376 main workers, which accounts for 82.5% of the workforce. Within this group, 22,751 individuals (19.6%) were engaged as cultivators, working on their land or supervising agricultural activities. There are 56,192 persons working as agricultural laborer, accounting for 48.3% of the major workforce. These people collect wages from people whose farms they help tend. Additionally, 2,600 individuals (2.2%) were involved in household industries, which include small-scale and home-based production activities. The remaining 34,833 workers (29.9%) were categorized as "other workers," which covers a variety of occupations beyond agriculture and household industries, such as services, construction, trade, and transportation.

LULC mapping

For this study, LULC maps of the study area are created using clear georeferenced satellite images from 2011, 2014, 2017, 2020, and 2022. A visual interpretation method, guided by the National LULC classification system, is employed to categorize the land into five primary classes: settlement areas, agriculture, wastelands, forests, and water bodies. Further, the agricultural area is categorized into cropland, fallow land, and plantations. The LULC maps were prepared for the selected years 2011, 2014, 2017, 2020, and 2022 based on the crop calendar. Figure 3 illustrates the LULC of the study area for the year 2011 to 2022.

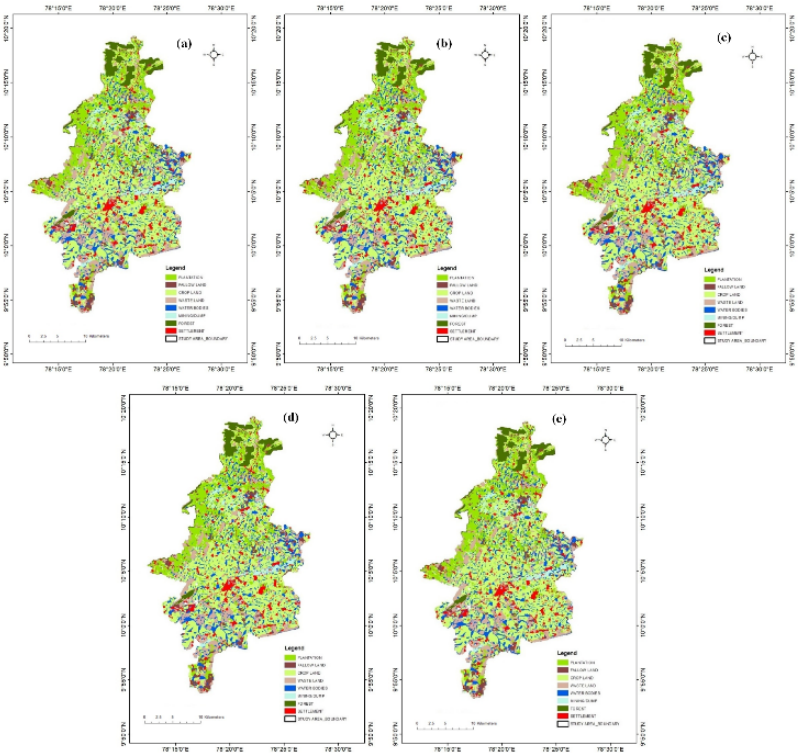

Figure 3. LULC of the study area for the year (a) 2011, (b) 2014, (c) 2017, (d) 2020 and (e) 2022.

Change detection analysis

The change detection analysis of different LULC categories, based on the National ranking scheme and their spatial coverage, have been analyzed using satellite-derived maps, as shown in Table 8.

Table 8. Changes in LULC area in square kilometers.

Category/ Year	2011	2014	2017	2020	2022
Settlement	24	34	37	40	56
Forest	27	26	26	25	25
Water bodies	93	91	89	81	81
Cropland	321	299	295	295	294
Fallow land	17	21	24	24	24
Plantations	108	115	115	117	96
Wasteland	81	85	85	89	95
Others	10	10	10	10	10

Accuracy assessment of LULC maps

LULC maps created through RS inevitably contain some level of error, which can arise from various factors, including the data capture process and the classification methods employed. To understand these errors quantitatively, it is essential to assess classification precision. A widely used approach for evaluating classification accuracy is the error matrix. In this study, the accuracy assessment for the year 2022 land use map is based on ground truth data, while the accuracy for maps from 2011, 2014, 2017, and 2020 is evaluated using reference points corresponding to those specific years. The Kappa coefficients (K) for the land use maps demonstrate a strong level of agreement, with values recorded as 0.83 in 2011, 0.86 in both 2014 and 2017, 0.88 in 2020, and 0.95 in 2022. The OA percentages calculated for the study area are 86 % for 2011, 88 % for 2014, 88 % for 2017, 90 % for 2020, and 96 % for 2022, as presented in Table 9.

Table 9. Accuracy assessment of LULC maps.

LULC class	Land use map year 2011		Land use map year 2014		Land use map year 2017		Land use map year 2020		Land use map year 2022	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Settlement	100	100	100	100	100	100	100	100	100	100
Forest	80	80	80	80	80	80	100	100	100	100
Water bodies	100	100	100	100	100	100	100	100	100	100
Cropland	80	88.90	90	90	90	90	90	90	90	90
Plantations	85.70	85.70	85.70	100	85.70	100	85.70	100	85.70	100
Fallow land	80	66.67	80	66.67	80	80	80	66.80	100	100
Wasteland	85.70	85.70	85.70	85.70	85.70	75	71.40	71.40	100	87.50
Others	80	80	80	80	80	80	100	100	100	100
OA (%)	86		88		88		90		96	
K	83.80		86.16		86.16		88.47		95.38	

Agriculture dynamics modelling

MATLAB provides an easy-to-use platform for developing and training ANN models, allowing customization of the framework, such as the unit of layers, neurons, and learning algorithms. The outputs derived from the given data are presented in Figure 4. Before training the model, normalization of all input features was performed to avoid scale bias and improve learning efficiency. Also, this prevents certain features from dominating others during the training process and helps the ANN learn more efficiently. The ANN model used was a feedforward architecture that was trained by the backpropagation algorithm. The network structure and the number of hidden layers were optimized by trying different combinations of neurons, and early stopping was applied to avoid overfitting. The calibration of the model was accomplished through trialand-error to equal the predictions and observed LULC maps. The generalizability of the model and the strength of its classification were evaluated with the help of Cross-validation methods and ROC-AUC scores. Once trained, the model classifies existing LULC categories and predicts future changes based on historical data. The data preparation consists of two types: i) Input data, these are the feature datasets that influence LULC, such as satellite image bands, indices, temperature, rainfall, soil, and socio-economic parameters; ii) Target data, these represens the LULC categories. Based on the model, the target data can be provided as categorical values or in a one-hot encoded format for classification purposes.

Normalizing input data before training an ANN is an essential step to lift the model's capability and precision and ensure that no single feature with a larger value range dominates the training process. In this research, the model inputs, such as physical, environmental, and socio-economic parameters, were normalized for better results. The neural network used in this study consists of an input layer with 8 neurons and an output layer with 1 neuron. The feedforward architecture was used, and the proposed model was trained using a backpropagation algorithm. The backpropagation algorithm was used to maximize learning performance and minimize error. The hidden layer structure was designed to strike a balance between model complexity and computational cost. Structures were tested for optimal structure to make good predictions. Various neuron combinations were tested to increase performance. When a single hidden layer was used, the number of neurons was between 5 and 12. When two hidden layers were used, the first had between 8 and 12 neurons, and the second had between 4 and 8 neurons.

The suitable structure was arrived at based on the model's capacity to generalize to new data. The number of training epochs was determined by assessing model convergence and preventing overfitting. Initial training began with 100 to 500 iterations to evaluate performance over multiple runs. Early stopping was applied to terminate training when validation performance ceased to improve, reducing the risk of overfitting. Additionally, the learning rate was fine-tuned within the range of 0.001 to 0.01 to ensure stable and efficient training. To identify the most effective architecture, configurations ranging from 3 to 7 neurons per layer were explored and evaluated based on model performance. Mean squared error (MSE) was employed for regression tasks to quantify the model's predictive accuracy.

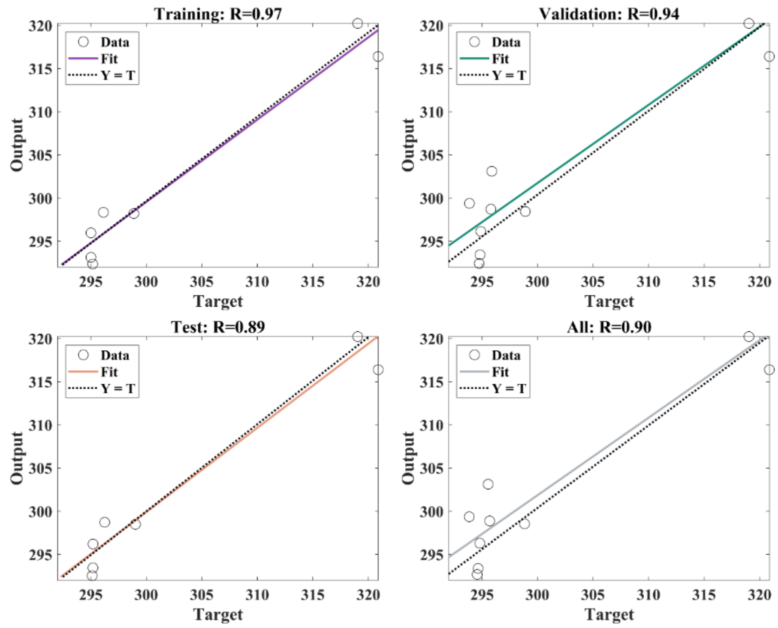

Figure 4. Overall LULC model output.

As shown in Figure 5, the accuracy and loss measures over training epochs are used to evaluate the trained ANN model's performance. The training and test loss values across 100 epochs are displayed in the loss plot. The effective learning is shown in Figure 5a, which exhibits a reduction in the first 20 epochs before stabilizing around the 30th epoch. The batch-based optimization effects are suggested by slight variations that last beyond 50 epochs. Both training and test accuracy were improved, according to Figure 5b. After 30 epochs, the accuracy plot shows improvement, indicating a good learning capacity of 95 to 100%. The minimal overfitting is shown by training and test curve alignment. The model is appropriate for predicting tasks because it achieves optimum generalization.

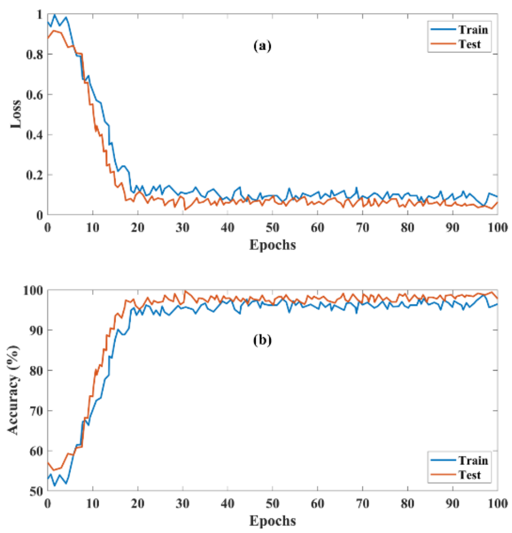

Figure 5. ANN model's performance (a) loss plot and (b) accuracy plot.

Significance of input parameters

Sensitivity analysis plays a major role in determining the comparative significance of the input variables in predicting the ANN model. This study applied a structured perturbation-based sensitivity analysis procedure to determine the proportion of individual input drivers to the predictive output of the model. It is a method of increasing model transparency and aiding in the determination of the prevailing variables that drive agricultural land use change. The perturbation method perturbed/varying one input parameter at a time by 5, 10, and 20%, holding all other inputs fixed. This enabled the isolation of the influence of each of the variables on output land use classification. Each variation was re-run in the ANN model, and the resulting changes in MSE and changes in classification accuracy were recorded to gauge sensitivity. It was observed that the socio-economic parameters had the overall greatest influence, with a 17.74% contribution to the variation in output. Important socio-economic indicators were the growth of population, literacy rate, and sex ratio. Vegetation indices, including NDVI (12.52%), EVI (12.26%), and SAVI (11.4%), were also highly sensitive as they are directly related to the health condition and productivity of the land cover. The climatic conditions also have a moderate yet significant influence, with groundwater level contributing 11.65%, rainfall contributing 9.91%, and temperature contributing 9.22%. In order to allow sensible comparison among variables, the resulting sensitivity scores were transformed to a cumulative scale of 100%. This procedure not only prioritized the drivers according to their influence but also confirmed the soundness of the ANN model by showing a consistent reaction to ecologically and socio-economically meaningful inputs. Altogether, the sensitivity analysis reassures that a set of socio-economic and biophysical drivers control the land use dynamics in the study area, and it is reasonable to include them in the predictive modelling framework. This understanding can be utilized to set priorities in data collection and guide future land policy interventions.

Predicted LULC *vs* ANN model

An ANN model was used to predict land use changes for the years 2033 and 2044. The model was trained using LULC data from 2011 to 2022, along with projected driving factors from 2022, to estimate future land use patterns. To ensure reliability, the model was calibrated and validated using satellite-derived land use maps for the predicted years 2033 and 2044, as shown in Figure 6, and achieved an OA of 90%, as shown in previous Figure 4. The results indicate a rise in settlement areas, which are projected to reach 12.92% by 2033 and 17.62% by 2044. In contrast, agricultural land, including cropland, plantations, and fallow land, is expected to decline by 42.5% in 2033 and further decrease to 51.4% in 2044. Wasteland is projected to increase to 16% by 2033 and 18.06% by 2044. Additionally, forest cover and water bodies are expected to experience slight reductions of 3.38% and 3.08%, respectively, in 2033, with more significant decreases of 10.13% and 8.37% by 2044.

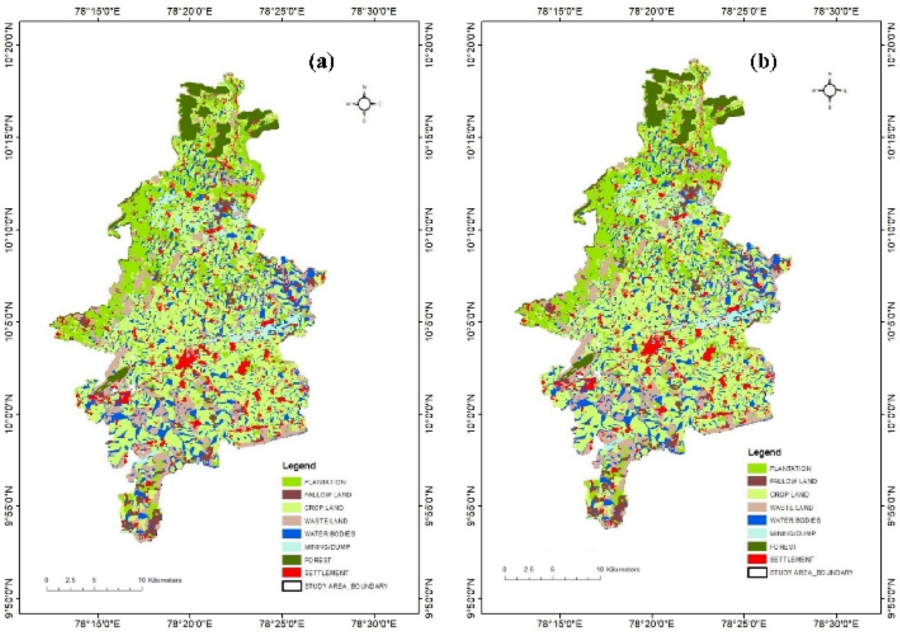

Figure 6. Predicted LULC maps for years (a) 2033 and (b) 2044.

Conclusions and future scope

Based on the results of this study, the following conclusions are drawn with respect to the LULC classification and ANN modelling of the study area.

- Time series analysis, specifically using ANN models, has been found to be a crucial tool for examining both current and projected patterns in the physical, environmental, and socio-economic sectors.
- In creating LULC maps, a visual interpretation of images yielded an OA rate between 86% and 96%.
- The study has highlighted significant shifts across primary land use categories over a period spanning from the years 2011 to 2022. The middle and southern regions of the research area showed the most noticeable changes.

- The analysis suggests an upward trend in factors such as culture, education rate, sex ratio, non-working population, and workforce size in future projections, while the number of agricultural laborers and cultivators is likely to stabilize by 2033 and 2044.
- This study highlights the role of MSE and correlation coefficients in pinpointing the factors influencing shifts in patterns of land usage.
- Among the drivers evaluated through correlation, no single factor is found to impact all land use types uniformly. The link between LULC types also fluctuates over different years.
- The impact of various drivers on land use changes has shown variability, with socio-economic factors and climate having notable influence. The population has emerged as the primary driver, followed by factors such as infrastructure availability, groundwater levels, the proportion of cultivators, and literacy rates.
- Including socio-economic variables in the analysis of agricultural land use provided a significant enhancement in explaining overall changes, suggesting that these variables are robust predictors of agricultural land trends, especially when analyzed alongside climate-related factors.
- An analysis is conducted to investigate the relationships between changes in agricultural land use, climate conditions, and socio-economic factors individually and in combination.
- Although climate variables, such as temperature and rainfall, play a role in agricultural activities, their correlation strength is relatively weaker compared to that of socio-economic data due to their coarse nature.
- An ANN model for LULC integrated with MSE and correlation coefficients proved highly effective for forecasting land use changes.
- Time series analysis using the ANN model is found to be an essential tool for examining current and future trends in physical, environmental, and socio-economic variables. This model has been applied to project climate patterns and socio-economic drivers for the years 2033 and 2044, providing critical data inputs for forecasting land use changes expected in 2033 and 2044.
- The input parameters for the ANN model developed in this study are rainfall, temperature, groundwater, population growth, sex ratio, literacy rate, working & non-working participants, NDVI, EVI, and SAVI. The significant input variables in decreasing order are population growth, sex ratio, literacy rate, NDVI, EVI, SAVI, groundwater,

- rainfall, and temperature. The output from the proposed model is the LULC pattern in any desired future year.
- Assessing ANN model accuracy is essential in studies like these to ensure reliable projections. Simulation models are particularly useful in identifying the extent of future changes within the most dynamic LULC categories.

The primary challenge faced in this research is the difficulty in accessing high-resolution, multi-temporal images, which are essential for enhancing classification accuracy and, subsequently, the model's reliability in simulation. Another significant problem is the lack of multi-temporal ground truth data for the past few years, which is necessary for conducting accurate supervised classifications. Model performance will be evaluated at both low and high resolutions to assess the impact of cell size on potential errors. These factors present compelling areas for further research. Utilizing multi-temporal datasets allows for more detailed classification levels, such as distinguishing between cropland, plantations, and fallow land. This approach can better reveal how seasonal climate variations influence rain-fed agricultural practices. For a country like India, where agriculture plays a central role, it's essential to consider water sensitivity in long-term planning to sustain economic growth and meet the food demands of a population projected to grow significantly by 2050.

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