Pol. J. Environ. Stud. Vol. 31, No. 3 (2022), 2779-2786
DOI: *10.15244/pjoes/141810* ONLINE PUBLICATION DATE: 2022-03-23

Original Research

Assessment of Land Use and Land Cover Dynamics Using Geospatial Techniques

Dinagarapandi Pandi[1], Saravanan Kothandaraman[1]*, Muthukrishna Vellaisamy Kumarasamy[2], Mohan Kuppusamy[1]

[1]School of Civil Engineering, Vellore Institute of Technology, Chennai-600127, India
[2]Civil Engineering Programme, School of Engineering, University of KwaZulu-Natal, Durban, South Africa

Received: 31 March 2021
Accepted: 30 August 2021

Abstract

Land Use and Land Cover (LULC) changes are important for sustainable water and land resources management. In this study, an attempt is made to perform quantitative analysis of past and future LULC changes at catchment scale. A case study is taken over Chittar catchment a tributary of Tharamirabarani river basin, Tamilnadu of India. In this study, LULC is grouped as per NRSC Level 1 scheme consists of five sub classes viz. built up land, agricultural land, waste land, water bodies and forest land. The 2000 and 20005 LULC maps are used as base maps to determine the transition potential. Then, CA-ANN is espoused to forecast the LULC for the year 2010. The kappa statistics is used to measure the spatial accuracy between forecasted and historical LULC for year 2010. The overall spatial matching between the two LULC is 91% and the kappa coefficient is 86%. From the total 30 years of past and future LULC, almost 58% of area is covered with the agricultural land, followed by 16% of forest, 15% of waste land and 11% of built up and water bodies. Change detection analysis is carried out at 10 and 30 years interval. This LULC change analysis is important for hydrological model development and land resources management.

Keywords: LULC, CA-ANN, change detection, Chittar catchment

Introduction

Water and land are the two natural resources which are highly stressed in most of the developing countries like India, South Africa etc [1-6]. Land Use and Land Cover (LULC) changes have a direct and significant impact on the two natural resources. The LULC changes are triggered by the manmade, climate and environmental factors [7]. The LULC changes are essential to fulfil the demand of food, water and sheltering needs of growing population. In addition, LULC changes have also been linked to social-economic development of a region. Water and land are hydrologically connected in a natural system called catchment. Catchment scale time series of LULC mapping and changing detection analyses helps to detect the extent of natural and human influence on the two natural resources [2, 3, 6, 7]. Unplanned LULC changes increase the recurrence of disaster such as flood, drought, landslides, land subsidence, soil erosion etc [1, 3, 6]. It is also altering the hydrological process over a catchment which in term to play an important role

*e-mail: sarav.gw@gmail.com

in developing catchment scale hydrological model [6]. Further LULC changes are significantly controlling the spatiotemporal water quantity and quality at catchment scale. The spatiotemporal changes of LULC is impotent for variety of purposes such as developing hydrological model, disaster management, urban planning, irrigation management, environmental impact assessment, damage assessment etc [6-8]. The change detection analysis is one of way to quantify the spatiotemporal LULC changes systematically. Lu et al. [9] discussed the various frameworks for change detection analysis. Supervised classification, principal component analysis, fuzzy classification and post classification methods are the most frequently used change detection analysis algorithms [10]. Among the modern technologies available for change detection analysis, the combined use of remote sensing satellite data and geospatial technology has been proven to be robust, economical and least time consuming process [1-5]. Nowadays high resolution remote sensing satellites data such as Resourcesat, Landsat and Sentinel 2 are available freely. The Landsat is launched with 30 m spatial resolution with Visible to Near Infra-Red (VNIR) sensors by the Earth Resources Observation and Science Centre, NASA; it's accessible globally and has its best service on the land and water resources management [2, 5, 10, 11]. The Sentinel 2 has its services in monitoring the morphology of land and it has a succession of 10 m spatial resolution VNIR by the European Space Agency. An enormous amount of information is delivered by the Landsat (Earth observation satellite) data providing the information in an exceptional amount regarding the biosphere and the earth surface. The Landsat imagery available from the early 1970s and provides a repeated cycle of 8 days [10-12]. Landsat imagery has the data series of Multi-Spectral Scanner (MSS), Landsat Thematic Mapper (TM), Landsat Enhanced thematic mapper (ETM) Landsat Enhanced thematic mapper plus (ETM+) and Landsat Operational land imager (OLI). They have the 30m of spatial resolution and VNIR regions covers blue (0.45-0.52 micrometer), green (0.52-0.60 micrometer) and red (0.63-0.69 micrometer). The VNIR regions were generally used to classify the land use pattern [13]. Mohajane et al. [14] used Landsat TM, ETM, ETM+ and OLI by applying Normalized Difference Vegetation Index (NDVI) map and using maximum-likelihood supervised classification to estimate the vegetation change over Azrou forest in the Middle Atlas, Morocco. Lone and Mayer [15] used the Indian Remote Sensing Linear Imaging Self-Scanning System III and Resourcesat-1 imagery to classified the LULC by applying supervised classification techniques. Timm Hoffman et al. [6] performed the long-term LULC change detection using Landsat imagery. They found a decrease in forest and agricultural areas over Karoo drylands of South Africa because of intensified urbanization and industrial development. Eludoyin and Iyanda [16] studied the land cover changes using Landsat imageries over Ife forest reserves in Nigeria. The outputs of the study provide strategies guideline for forest management in this area. Jayakumar and Arockiasamy [17] conducted remote sensing and GIS based LULC and change detection analyses over Kolli hill, part of Eastern Ghats, India. Through this study they suggested future plan for sustainable land resources management and development.

Many researchers reported that LULC and climate changes are the two important factor that alter hydrological system changes through their impact on water balance components viz. runoff, infiltration, evapotranspiration, soil moisture etc. [2, 3, 18]. Popular modelling packages for LULC forecasting are IDRISI's CA-MARKOV, Dyna-CLUE, Celluar Automata (CA)-ANN etc. CA-Markov model is mostly applied for land use change detection analyses [4, 18-20]. The CA-ANN model is mostly used to access the spatial changes over time with the help of neighbourhood pixels and a transition map of the LULC [5, 8]. Yirsaw et al. [21] studied the impacts of LULC changes over Su-Xi-Chang region, China and the subsequently analysed the spatial changes in ecosystem service value. Aarthi and Gnanappazham [22] have taken a case study using CA-ANN to study the urban growth over upper catchment of Thamirabarani lies at the Western Ghats India. They used LULC data for the period 1996-2016 to forecast the LULC for the years 2025 and 2030. The objective of the present research is to perform quantitative analysis of past and future LULC at catchment scale. To meet the objective the future LULC data is derived from historical remote sensing satellite data using CA-ANN algorithm. The kappa statistics is to measure performance of the LULC model. Further to demonstrate the capability of the model a case study is taken over Chittar catchment a tributary of Tharamirabarani river basin, India. The model output is most useful for developing hydrological models, water and land resource management and development.

Materials and Methodology

Study Area

Chittar catchment lies in the global coordinates of 77º9'E and 9º12'N to 77º48'E to 8º48'N. It is part of Tharamirabarani river basin, southern Tamilnadu state, India (Fig. 1). This catchment comprises of about 78% agricultural land. Chittar catchment covers the few towns such as Sengottai, Tenkasi, Kadayanallur, Alankulam etc. The study area boundary delineates form the A P Puram gauge river discharge station using geographical information system (GIS). The study area is divided into five sub classes such as built up land, agricultural land, waste land, water bodies and forest land. The total area is covers about 1291 sq.km. Thereby, catchment is fed by the northeast monsoonal rain, as it carries rain water only during September and December [23].

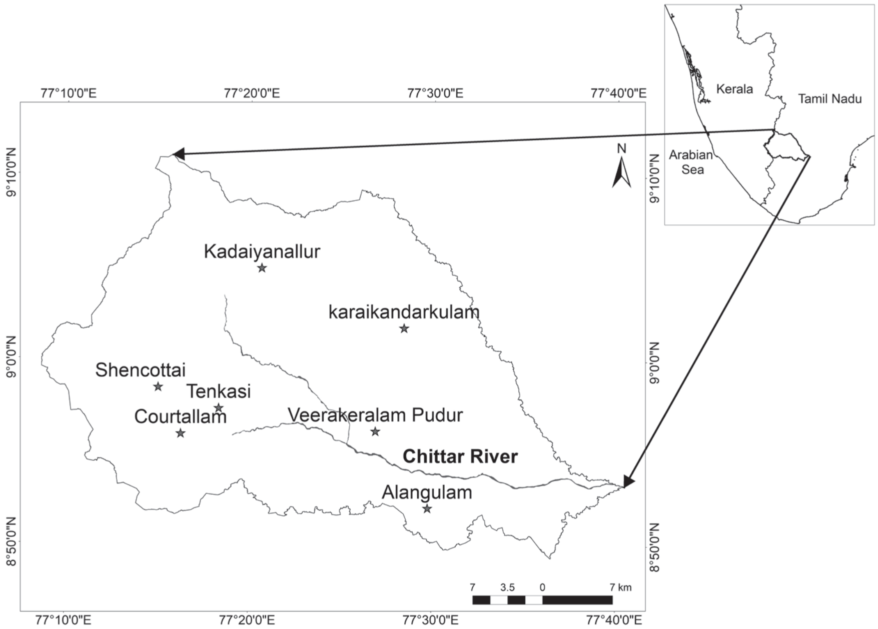

Fig. 1. Location map of the study area.

LULC Preparation

The time series of Landsat imagery such as TM (image dates: 14, December 2000 & 18, May 2005), ETM (image date: 2, October 2010) and OLI (image dates: 7, October 2015 & 9, April 2020) are used in this study. The Landsat imagers used in this study are 30 m resolution and downloaded from U.S. Geological Survey Earth explorer. All imageries are projected by Universal Transverse Mercator (UTM) zone 44 N in World Geodetic System (WGS) datum (WGS_1984_ UTM_Zone_44N) to ensure consistency between datasets. In this study, LULC is classified as per Level 1 National Remote Sensing Centre (NRSC) guidelines. The Level 1 classification scheme consists of five sub classes [24]; they are built up land and agricultural land consider as land use, waste land, water bodies and forest consider as land cover. These sub classes prepared with the supervised classification method [14]. Supervised classification is usually applied with the trained algorithm; maximum-likelihood classifier is gathering each trained pixels of Landsat imagery [10, 15]. Maximum-likelihood classifier is on the most popular criteria in supervised classification method. It is a statistical based learning algorithm to assist the classification overlapping signature pixels to the feature based on maximum-likelihood [6, 25]. In this study, maximum-likelihood classifier of supervised classification is applied those trained pixels and delineated the LULC maps for the years 2000, 2005, 2010, 2015 and 2020 over the Chittar catchment. The LULC classification performed in QGIS software using Semi-automatic Classification Plugin (SCP). The SCP is one of the popular QGIS open source plugin to perform supervised classification.

LULC Forecast

Present study, CA-ANN [5, 8, 26] is used to forecast the LULC over the Chittar catchment. The recently developed MOLUSCE (Modules for Land Use Change Simulations) an open source plugin of QGIS is used to process the CA-ANN model [5]. This plugin supports four popular algorithms such as ANN, weights of evidence, multi-criteria evaluation and logistic regression. The multi-layer ANN model performance generally relies on the parameters such as neighbourhood, learning rate, momentum, maximum iterations number and hidden layers. An ANN training datasets can set arbitrary number of hidden layers (one or more) and arbitrary number (one or more) of neurons in the layers. The guideline for assigning number of input neuron is as follows:

$$(C_f - 1)(2N_b + 1)^2 + R_f(2N_b + 1)^2 \quad (1)$$

where C_f = number of LULC sub classes, N_b = assigned neighbourhood pixels size, R_f = summary band count of factor raster's. Output neurons usually are a count of unique sub classes in the LULC map. The training datasets uses the classic back propagation algorithm with momentum for the learning procedure. Trained data rectification is performed as follows

$$X(n + 1) = \mathrm{L}_r * D_x (n) + m * D_x (n - 1) \quad (2)$$

where X = vector of neuron weight in trained data, D_x = vector of neuron weight changes, n = iteration number, L_r = learning rate, m = momentum.

The initial and target LULC data is used to find the transition potential. Analysis of transition potential is determined from the areal changes between the LULC sub classes. ANN model is used to determine the transition potential of LULC sub classes [27]. Then, Cellular Automata (CA) is one of the techniques used for forecast the data by adopting the arrived transition potential. Kappa statistics is used to validate the model output through multi-resolution budget [8]. Kappa statistics is one of the popular methods to check the accuracy level of two spatial raster data [10, 23].

Change Detection

Change detection is the comparison of two raster that can be matching with multi-temporal resolution. GIS platform helps to overlay the two datasets and find out the LULC sub classes changes over the study area. Generally, image differencing, comparison, kappa statistics and principal component techniques are quantifying the LULC changes between two multi-temporal LULC maps [25]. In this study, kappa statistics is used to quantify the LULC changes between multi-temporal LULC maps by measuring the spatial matching accuracy assessment. Accuracy assessment deals to analyse with the Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA) and overall spatial mismatching. Finally, the kappa coefficient can be analyzed between the two datasets [10, 23].

Results and Discussion

To demonstrate the application of the proposed methodology a case study is taken over the Chittar catchment. Chittar river originating on the Courtallam hills of Eastern Ghats in the Tamilnadu state of India. Upper catchment has the steeper slope [28], so the rain drains towards the plain area. The LULC maps for the years 2000 and 2005 are used as initial and target maps to determine the transition potential. Then, CA-ANN is espoused to forecast the LULC for the year 2010. To validate this method kappa statistics are used to quantifying spatial matching between historic and forecasted 2010 LULC sub classes. The UA provides spatial matching of forecasted 2010 LULC with historical 2010 LULC and PA provides the matching vice versa. In this study, it is found that both UA and PA for all five LULC sub classes are more than 70%. The overall average spatial matching between the two LULC is 91% and the kappa coefficient is 86%. The kappa coefficient more than 50% can be considered as satisfactory [10, 23].

Historical LULC

The dynamic of area contribution in percentage of each sub class is shown in Fig. 2 for the years 2000, 2005, 2010, 2015, 2020, 2025 and 2030. To make it better, year- wise area contributing in sq.km for each sub class is also provided in Fig 2. The agricultural and forest land jointly covers about 77 % of the catchment area. The remaining 23 % is covered by waste land (18 %), water bodies (3%) and built up land (2%) as shown in the Fig. 2. Agricultural land and forest are more prominent for producing the evapotranspiration [4, 29]. Mishra et al. [25] explained that the agricultural and forest land are predominant change users by the manmade as well as natural landforms. The agricultural and forest land changes lead to cause the critical environmental issues, likely as soil water scarcity over the catchment. Historical

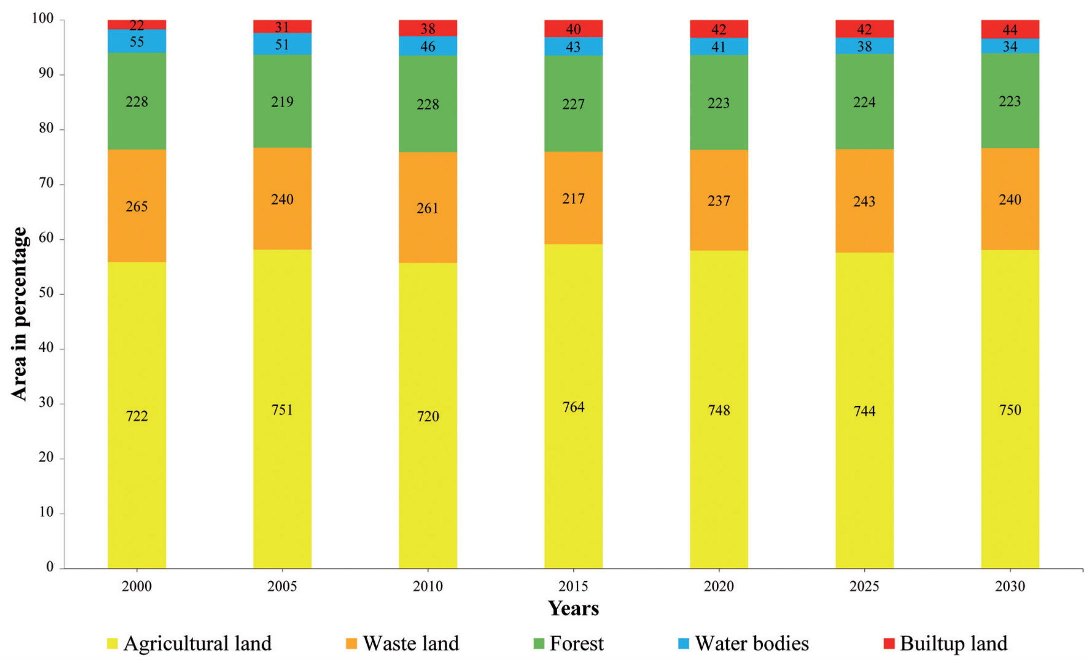

Fig. 2. Five year LULC dynamic from 2000 to 2030.

LULC of 2000 and 2005 shows the agricultural land increases. During this period, irrigation management was active in the region as there were several dams and irrigation canal systems were constructed. As result of this irrigated area is expanded during this period. Later, agricultural land slowly decreases may be due to scanty rainfall caused by the monsoon failure. It led to low agricultural productivity. Here, agricultural land of 2015 is gradually increasing with 2.5% from 2000 and simultaneously waste land is decreased by 10 % for the same period. The conversion of waste to agricultural land is more dominant for an increase in farming activities [30]. From 2000 to 2015, 0.1% of the forest is converted to waste land; thus, it leads to more runoff due to deforestation in the foot hills [25]. The 90% area (about 20 sq.km) of built up land over Chittar catchment increases from 2000 to 2020 due to population growth. Built up land is converted from the agricultural and waste land.

The industrial development and population growth steadily increases the built up land over the catchment [6]. It is observed that built up area has increases about 20 sq.km from 2000 to 2020. From 2005 onwards the area of water body are steadily decreases. In the Chittar catchment, 16 % of water bodies (about 14 sq.km) are decreased between the periods of 2000 to 2020 and hence declines in the surface water resources. Results of this study show that the reduction of water body area is about 4 sq.km/year. This reduction may be due to the encroachment, pollution and lack of maintenance of water bodies.

Forecast LULC

The CA-ANN model is performed by the neural schemes that focus on the gain and loss of areal with in LULC sub classes. LULC change analysis is used to forecast the 2025 with the data's of 2015 and 2020, similarly 2030 with the data's of 2020 and 2025. Sample historical and forecasted LULC maps are shown in Fig. 3. The 6 % of waste land decreases from 2000 to 2030 and alternately increases in 3 % of agricultural land at the same period. For a long term, agricultural land is being sustained at their maximum areal coverage in the mid-lower portion of Chittar catchment. Thus, it defines the probability of low runoff and high evapotranspiration in over these areas [29]. From 2000, forest has decreased in 4 % area that converted into an agricultural land. Thus, forest area is transformed into waste land on 2015 and then has changed into agricultural land (about 1.5 %) due to farming activities. The built up area is gained (about 0.5 %) in 2030 to meet the demand of increasing population. However, total area of the forest land is almost stable. This result supporting those steps jointly taken by Government of India and State Government of Tamilnadu greatly helps the conservation of forest land. Finally, in 2030 area of water bodies in the Chittar catchment has decreased by 30% when compared to 2000. Water bodies have changed the built up and agricultural land due to encroaching activities of humankind. From the Fig. 2, an area of built up land and water body literally opposes each other according to their area consumption.

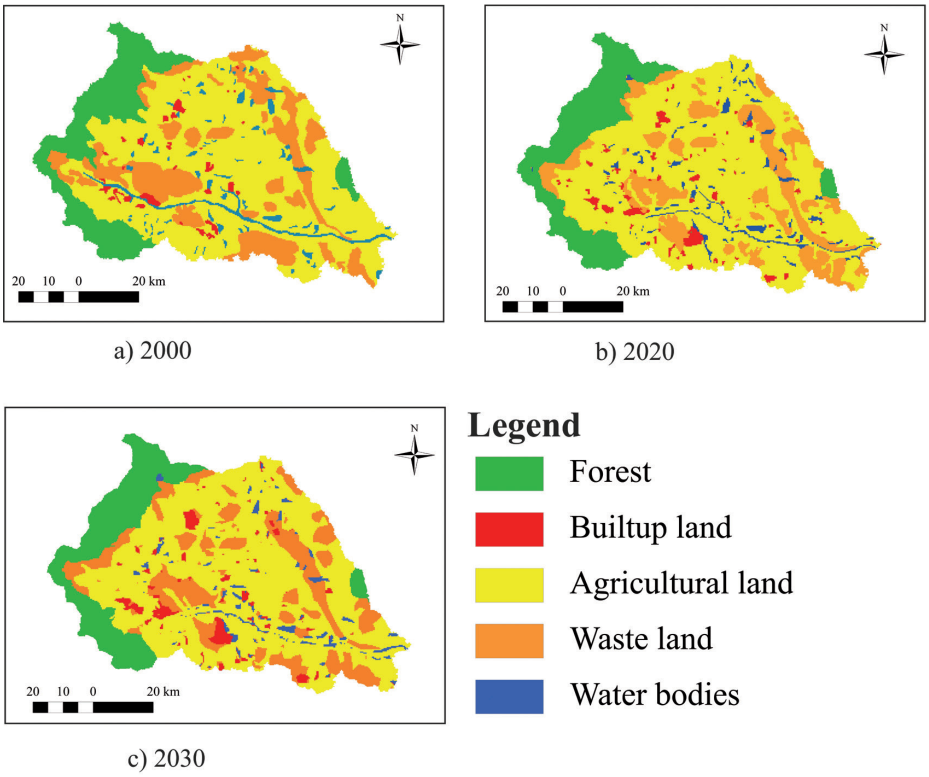

Fig. 3. LULC status of the catchment.

Table 1. LULC Change detection assessment.

LULC types	Area of gain (+) or loss (-) in sq.km				Kappa statistics							
					2000-2010		2010-2020		2020-2030		2000-2030	
	2000-2010	2010-2020	2010-2020	2000-2030	UA	PA	UA	PA	UA	PA	UA	PA
AL	-2	29	2	29	0.8	0.8	0.87	0.84	0.86	0.87	0.8	0.78
BL	16	4	2	22	1	0.54	1	0.74	1	0.78	1	0.31
FL	-1	-4	0	-5	0.93	0.94	0.92	0.94	0.93	0.96	0.88	0.93
WL	-4	-24	2	-25	0.55	0.56	0.61	0.68	0.67	0.65	0.52	0.58
WB	-9	-5	-6	-20	0.43	0.04	0.5	0.03	0.47	0.03	0.33	0.04

Abbreviation: AL – Agricultural land; WL – Waste land; FL – Forest; WB – Water bodies; BL – Built up land

Overall results show that LULC changes over period 2000-2030 are moderate in this study area due to lack of development over the catchment. After 2015, the waste land is being sustained and it is mostly salt affected area and lack of fertility. So this limits the conversion waste land to either built up land or agricultural land.

Agriculture land is one of the important factors that influencing the development of a country [18]. The agriculture land mostly converted in to build land to accommodate the increasing population and industrial development. The decline of agricultural land poses food security risks along with loss of rural employment [15]. So, agriculture area needs to be increased substantially to meet the food demand of increasing population. However, increase in agricultural area poses addition stress to land and water resources. Both scenarios cause social upheaval in a traditionally agrarian society and leads to unrest. So, LULC change analysis is helps the policy makers for sustainable development, including sustainable land and water resources management.

Change Detection

Systematic quantification of spatial and temporal LULC changes is important for sustainable development. Change detection is the process to delineate spatial LULC changes between the multi temporal images. Here, change detection analysis is carried for the period 2000 to 2030 over Chittar catchment between NRSC level-1 five sub classes. Table 1 summarises the area of gain (+) or loss (-) in sq.km and accuracy assessment between each sub classes. The trend of LULC changes for every 10 years and 30 years periods are reported in this study. For the period 2000 to 2010 water body experienced the highest changes, about 9 sq.km area converted to build-up area. It is observed that during this 10 years period built-up area is reclaimed from the remaining four sub classes. The change detection analysis revealed that the sub classes agricultural and waste lands are highly dynamic during the period 2010 to 2020. Approximately 24 sq.km of waste land is reclaimed in to agricultural land between 2010 to 2020. During this period it is observed that conversion of natural areas viz waste land, forest land and water bodies in to agricultural land and build up land. This conversion is driven by the increasing demand for food and sheltering requirements of the growing population.

In the present decade (i.e. 2020 -2030) about 6 sq.km of water body is converted in to built up land, agricultural land and waste land equally. This conversion is may be driven by the frequent failure monsoon rainfall in this region, lack of maintenance of small water bodies and encroachment. This will lead to additional stress to ground water along with reduction of natural recharge, flooding and soil erosion. The overall change detection analysis (2000 to 2030) show that forest land is the only subclass experienced the minimal changes. About 25 sq.km of waste land is reclaimed during 2000 to 2030. Further 20 sq.km water body is lost in same period. Agricultural land and built up land are two sub classes that gaining continuously during the three decadal periods. These results of three decadal change detection analyses are important for catchment scale hydrological model development [2].

Kappa statistics is implemented to analyze the LULC sub classes from this change detection process. In kappa statistics, UA (e.g. spatial matching of a sub class in 2000 with 2020) and PA (e.g. spatial matching of a sub class in 2020 with 2005) are used to determine the level of contribution within the sub classes [23] as shown in Table 1. Overall spatial mismatching between the multispectral images indirectly quantifies LULC changes. In this study, the estimated spatial mismatching are 0.24, 0.18, and 0.17 respectively for the decades 2000-2010, 2010-2020 and 2020-2030. Overall spatial mismatching during the period 2000 to 2030 is 0.24. The UA of built up land is always 1 and the PA varies from 0.31 to 0.78. It indicates a steady rise build-up land. The UA and PA of forest land are nearly equal and it's more than 0.9. This confirms that there is no gain or loss in forest land. Similarly agricultural land also UA and PA are approximately equal which confirms the minimum changes. Trigger change is occurred in the waste land and water bodies as per this UA and PA statistics.

Conclusion

Systematic quantification of LULC dynamic is important for sustainable water and land resources management and development. In this study, a geospatial technology assisted change detection analysis is performed for the past and future LULC development at catchment scale. To demonstrate the capability, a case study is taken over Chittar catchment a tributary of Tharamirabarani river basin, India. The LULC is forecasting from past Landsat imagery data using CA-ANN algorithm. The LULC maps for the years 2000 and 2005 are used as base map for forecasting LULC for the year 2010 using CA-ANN algorithm. The model performance is validated using kappa statistics by comparing historical and simulated LULC for the year 2010. The overall average spatial matching between the two LULC is 91% and the kappa coefficient is 86% (>50% model performance is satisfactory). The major outcome of case study is as follows:

1. The change detection analysis from 2000 to 2030 show that forest land is the only sub class that experienced the minimal changes.
2. The waste land and water bodies are two sub classes that experienced maximum changes. About 25 sq.km of waste land is reclaimed during 2000 to 2030. Nearly 20 sq.km water body is lost in same period.
3. Agricultural land and built up land are two sub classes tgaining continuously during the three decadal periods.
4. Agricultural land, waste land and water bodies are three sub classes that are mutually change themselves. This change may driven by the temporal and spatial distribution rainfall over this catchment.

Acknowledgments

Authors thank to School of Civil Engineering, Vellore Institute of Technology, Chennai, Tamilnadu, India, for providing research-related facilities to complete this research articles and Research Office, University of KwaZulu-Natal, South Africa for supporting this publications. Authors are thankful to Landsat series of data provider – USGS Earth explorer. Authors also thank anonymous reviewers for their suggestions to improve the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

References

1. RUKUNDO E., DOĞAN A. Assessment of Climate and Land Use Change Projections and their Impacts on Flooding, Pol. J. Environ. Stud. **25** (6), 2541, **2016**.
2. GARG V., AGGARWAL S.P., GUPTA P.K., NIKAM B.R., THAKUR P.K., SRIVASTAV S.K., KUMAR A.S. Assessment of land use land cover change impact on hydrological regime of a basin. Environ Earth Sci, **76** (18), 635, **2017**.
3. WAGNER P.D., KUMAR S., SCHNEIDER K. An assessment of land use change impacts on the water resources of the Mula and Mutha Rivers catchment upstream of Pune, India. Hydrol Earth Syst Sci, **17** (6), 2233, **2013**.
4. GIBSON L., MÜNCH Z., PALMER A., MANTEL S. Future land cover change scenarios in South African grasslands-implications of altered biophysical drivers on land management. Heliyon, **4** (7), p.e00693, **2018**.
5. MEASHO S., CHEN B., PELLIKKA P., TRISURAT Y., GUO L., SUN S., ZHANG H. Land use/land cover changes and associated impacts on water yield availability and variations in the Mereb-Gash River Basin in the Horn of Africa. Journal of Geophysical Research: Biogeosciences, **125** (7), p.e2020JG005632, **2020**.
6. TIMM HOFFMAN M., SKOWNO A., BELL W., MASHELE S. Long-term changes in land use, land cover and vegetation in the Karoo drylands of South Africa: implications for degradation monitoring. African Journal of Range & Forage Science, **35** (3-4), 209, **2018**.
7. TIZORA P., LE ROUX A., MANS G., COOPER A. Land use and land cover change in the Western Cape Province: quantification of changes & understanding of driving factors. In: Planning Africa 2016; Making Sense of the Future – Disruption and Reinvention, , Sandton Convention Centre, Johannesburg, 3-6 July **2016**.
8. RAHMAN M.T.U., TABASSUM F., RASHEDUZZAMAN M., SABA H., SARKAR L., FERDOUS J., UDDIN S.Z., ISLAM A.Z. Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh. Environ Monit Assess, **189** (11), 1, **2017**.
9. LU D., MAUSEL P., BRONDIZIO E., MORAN E. Change detection techniques. International Journal of Remote Sensing, **25** (12), 2365, **2004**.
10. JULIEV M., PULATOV A., FUCHS S., HÜBL J. Analysis of Land Use Land Cover Change Detection of Bostanlik District, Uzbekistan. Pol. J. Environ. Stud., **28** (5), **2019**.
11. DINAGARA PANDI P., SARAVANAN K., MOHAN K. Identifying runoff harvesting sites over the Pennar Basin, Andhra pradesh using SCS-CN method. International Journal of Civil Engineering and Technology, **8** (8), 65, **2017**.
12. CAI Y., ZHANG H., PAN W. Detecting Urban Growth Patterns and Wetland Conversion Processes in a Natural Wetlands Distribution Area, Pol. J. Environ. Stud., **24** (5), 1919, **2015**.
13. JENBERU A.A., ADMASU T.G. Urbanization and land use pattern in Arba Minch town, Ethiopia: Driving forces and challenges. GeoJournal, **85** (3), 761, **2020**.
14. MOHAJANE M., ESSAHLAOUI A., OUDIJA F., EL HAFYANI M., CLÁUDIA TEODORO A. Mapping forest species in the central middle atlas of Morocco (Azrou Forest) through remote sensing techniques. ISPRS International Journal of Geo-Information, **6** (9), 275, **2017**.
15. LONE S.A., MAYER I.A. Geo-spatial analysis of land use/land cover change and its impact on the food security in District Anantnag of Kashmir Valley. GeoJournal, **84** (3), 785, **2019**.

16. ELUDOYIN A.O., IYANDA O.O. Land cover change and forest management strategies in Ife nature reserve, Nigeria. Geojournal, **84** (6), 1531, **2018**.
17. JAYAKUMAR S., AROCKIASAMY D.I. Land use/land cover mapping and change detection in part of Eastern Ghats of Tamil Nadu using remote sensing and GIS. J Indian Soc Remote Sens, **31** (4), 251, **2003**.
18. TOLESSA T., DECHASSA C., SIMANE B., ALAMEREW B., KIDANE M. Land use/land cover dynamics in response to various driving forces in Didessa sub-basin, Ethiopia. Geojournal, **85** (3), 747, **2020**.
19. HAMAD R., BALZTER H., KOLO K., Predicting land use/land cover changes using a CA-Markov model under two different scenarios. Sustainability, **10** (10), 3421, **2018**.
20. KITYUTTACHAI K., TRIPATHI N.K., TIPDECHO T., SHRESTHA R. CA-Markov Analysis of Constrained Coastal Urban Growth Modeling: Hua Hin Seaside City, Thailand. Sustainability, **5**, 1480, **2013**.
21. YIRSAW E., WU W., SHI X., TEMESGEN H., BEKELE B. Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the Su-Xi-Chang Region. Sustainability, **9** (7), 1204, **2017**.
22. AARTHI A.D., GNANAPPAZHAM L. Urban growth prediction using neural network coupled agents-based Cellular Automata model for Sriperumbudur Taluk, Tamil Nadu, India. The Egyptian Journal of Remote Sensing and Space Science, **21** (3), 353, **2018**.
23. DINAGARAPANDI PANDI., SARAVANAN KOTHANDARAMAN., MOHAN KUPPUSAMY. Delineation of potential groundwater zones based on multicriteria decision making technique. Journal of Groundwater Science and Engineering, **8** (2), 180, **2020a**.
24. ROY A., INAMDAR A.B. Multi-temporal Land Use Land Cover (LULC) change analysis of a dry semi-arid river basin in western India following a robust multi-sensor satellite image calibration strategy. Heliyon, **5** (4), p.e01478, **2019**.
25. MISHRA P.K., RAI A., RAI S.C. Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. The Egyptian Journal of Remote Sensing and Space Science, **23** (2), 133, **2020**.
26. QIANG Y., LAM N.S. Modeling land use and land cover changes in a vulnerable coastal region using artificial neural networks and cellular automata. Environ Monit Assess, **187** (3), 57, **2015**.
27. MAS J.F., KOLB M., PAEGELOW M., OLMEDO M.C., HOUET T., Modelling Land use/cover changes: a comparison of conceptual approaches and softwares. Environmental Modelling and Software, **51**, 94, **2014**.
28. DINAGARAPANDI PANDI., SARAVANAN KOTHANDARAMAN., MOHAN KUPPUSAMY. Factor analysis based prioritization of morphometric parameters at sub-watershed level. Water and Energy International, **63** (9), 52, **2020b**.
29. NUGROHO P., MARSONO D., SUDIRA P., SURYATMOJO H. Impact of land-use changes on water balance. Procedia Environmental Sciences, **17**, 256, **2013**.
30. AWOTWI A., YEBOAH F., KUMI M. Assessing the impact of land cover changes on water balance components of White Volta Basin in West Africa. Water Environ. J., **29** (2), 259, **2015**.