Review of Approaches for Assessing Changes in Land Use and Land Cover

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Abstract

As LULC change, it is important to consider the relationship between people and the natural world. More data is being gathered by researchers as a result of the significant regional changes and technological improvements. The combination of remote sensing and GIS technological improvements has made it simpler to follow changes in land use and cover from the past to the present. The application of this technology to identify regional and global trends has produced significant benefits for science. Remote sensing has used a variety of different change detection strategies in the past, and more effective techniques are always being researched. The primary tools for learning about LULC change in recent decades are the results of remote sensing satellites, which usually use multiple techniques based on the study goals. In any sensors project, picking a strong change detection strategy is strongly advised. The pre- and post-classification change detection techniques utilised for processing LULC information at the geographical area are covered in this review study paper.

Keywords: Land Use Land Cover (LULC), Geographical Area, GIS (Geographic Information System), Change Detection and Remote Sensing

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I. INTRODUCTION

Variations in land use cover, one of the fundamental factors of surroundings change on a global scale, are at the focus of the debate over environmentally friendly development. A number of viewpoints on the subject have been explored in order to pinpoint the components that influence to land use–land cover change, as well as its path and effects. Urban development, Long regarded as an indication of regional economic growth is the relocation of residences and commercial property to rural areas on the outskirts of major cities. Humans have historically investigated the environment at large and their capacity to spot changes in (LULC) [1]. On Earth's surface, a change in LULC brought on by the actions of humans is referred to as such. In probe of better life situation, employment opportunities, and accessibility to high-quality healthcare, people migrate from rural to urban locations. Urbanization results from this process of transition. The Repercussions of this urbanization have been detrimental to the environment, the economy, and society [2]. Therefore, it is crucial for academics and politicians everywhere to keep an eye on and lessen the adverse effects of LU/LC fluctuations for a number of management and scheduling jobs [3].

GIS and remote sensing are often used together to produce more accurate and detailed data about the surface the Earth. Remote sensing data can be comprise into GIS to create maps and visualizations that provide a comprehensive view of the Earth's surface. GIS, in turn, that can be used to analyze and interpret remote sensing data and to create models that can predict changes in the Earth's surface over time. Both GIS and remote sensing are important tools in the field of geospatial technology, and their integration has led to many applications in various fields such as natural resource management, disaster response, and urban planning. Remote sensing offers immense promise in land managing resources as a result of its low price and extensive time series data collection capacity over a broad contiguous area [4]. The most popular technique for determining land cover from remote sensing is random forest [5]. The Random Forest classifier can be used to categorise heterogeneous circumstances. RF is a simple-to-use classifier given that it just requires the customer to select two values as inputs. There are a lot of limitations on how accurate traditional land cover classification methods can be, as evidenced by numerous research [6].

II. LITERATURE REVIEW

A review of change detection methods
This section is organised into eight sections based on the land surface of the planet: The following are the eight factors: 1) vegetation, 2) delta region, 3) desertification, 4) urbanization, 5) mountain region, 6) watershed, 7} coastal zone, and 8) river flow.

Most research focused on how spatial LULC changes develop and how those changes impact the socioeconomic and environmental components of the area. To research and track LULC change and its effects on changing environmental situations, numerous change detection techniques have been developed. For the purpose of creating models and future projections of these changes, it is crucial to ascertain the reasons of and rate at which land use changes through time and space. The change detection methods covered in this study are also applicable to the categories of world regions that were previously established.

A. Vegetation

In this category, a range of change detection and prediction techniques have been examined. Large-scale plantation projects including orchards, agricultural lands, and forested areas all fall under this category.

The support vector machine (SVM) methodology was used for the land use categorization. There were decreases in agriculture and the forest of 3.07% and 14.01%, respectively [7]. The comparable Kappa values for the years 1990, 2010, and 2030 were 77%, 74%, and 73%, respectively, based on the categorization accuracy test results. Authors performed supervised classification on all of the photos using the maximum likelihood classifier (MLC) technique [8]. The study was looked at in a designated natural region in Calabria, Italy, and it's especially indicative of the ecology of the Mediterranean mountain forest. Researchers applied supervised pixel-based classification on Sentinel-2 pictures using the support vector machine (SVM), random forest (RF) and classification and regression tree (CART) methodologies. The spring picture composite with three Visusal Inertial System added to the Sentinel-2 bands (OA = 0.88 and Fm = 0.88) gave the greatest results when employing RF [9].

B. Delta region

This section has covered the review of delta regions and estuaries.
The Pensacola estuary ecology has been affected by major low urban expansion, and the examines coastal LULC alterations. Additionally, the population demonstrated an upward trajectory towards expansion throughout the research duration, which harms the waterway. In this, iso-data clustering and unsupervised classification were utilized [10].

C. Desertification

This category includes places affected by drought and dry terrain, which are examined.
This study found that the primary causes of sandy drought and erosion of land were human-caused processes [11]. Azraq Oasis in Jordan's desertification was observed. CVA and TCT are two techniques combined for change detection. The outcome revealed that bare soil expanded, accounting for more than 80% of the overall change [12].

D. Urbanization

Using the Change detection technique, the degree of land use class fluctuation between time intervals was compared. According to the findings, there was both an increase and a decrease in the number of different LU classes between 1986 and 2016. Overall, the results indicate that over the research period, urban areas expanded by 6.89% (18.47 km2) [13]. The categorization accuracy and Kappa coefficient results were satisfactory. Built-up regions, which integrate pixels with real structures, residential gardens, and trees , had the lowest user accuracy in 2006, coming in at 89.74% [14]. The study employed a cellular automata CA-Markov model to measure urban sprawl in the Indian city of Dehradun. In order to accomplish this, the spatial pattern of land cover change in the region was investigated using temporal LISS IV data. The data collected plainly suggest that built-up classes (around 27%) saw significant alterations between 2004 and 2009 [15]. In addition to forecasting the pattern of urban growth in Delhi and its surroundings, the investigation was focused on calculating the rate of environmental changes, their causes, and their effects. Using supervised maximum likelihood classifcation, it was possible to identify changes in land use and cover using Landsat satellite pictures from 1989, 2000, 2010, and 2020. Urban areas and open regions both increased by 13.44% and 2.40 percent, respectively, according to the change detection data [16]. Analyze the GIS-based land use change detection between 1985 and 2010 in Mansoura and Talkha. A change detection research revealed that whereas agricultural land declined by 33%, built-up area rose by more than 30%, from 28 to 255 km2. It employed both supervised and unsupervised categorization. In this supervised classification, the most likelyhood approach was used, and for unsupervised classification, the ISODATA clustering algorithm [17].

E. Mountainous region

This article reviews the studies on the high and low steep mountainous and hilly regions.
Thimphu, the capital city of Bhutan, is located at a high height. To determine the five land use classes for the city of Thimphu, both unsupervised and supervised (hybrid classification) methods were applied. As the precise number of pixels was unknown, hyper clustering was employed for unsupervised classification.Using the Maximum Likelihood Classifier (MLC) the output had then supervised sorted [18]. Recognition and forecasting changes in land usage along the Upper Siem Reap River in Cambodia. To examine changes in forest cover over the previous three decades a supervised maximum likelihood classification was used. Findings indicated that the forest class was deteriorating in comparison to more LULC classes. The kappa statistics value is between 0.75 to 0.79, and the overall classification accuracy ranges from 85% and 90% [19]. In ERDAS 9.3, the Maximum Likelihood Algorithm was utilized for picture classification. ArcGIS 9.1 was used for mapping and analysis of LULC groups. In the year 1990, the accuracy assessment revealed results ranging from 89.22 percent overall and 0.7783 Kappa accuracy, while the accuracy for the year 2005 image turned out to be 87.72 percent overall and 0.7633 Kappa [20]

F. Watershed

This category lists studies that pertain to watersheds.
This study comes to a finding that anthropogenic activities caused unintended changes that led to an increase in agriculture and settlement and a decline in water and vegetation. LULC change trends were discovered in the Ethiopian Beressa watershed. In order to improve LULC change analysis, Images from satellites were sorted using supervised categorization and post-classification

change detection techniques. As a result of government concessions given to households and towns, the results showed an immense rise of cultivation and settlement land while increasing the amount of forest cover [21]. This investigation looks for changes in the LULC patterns of the Chalus watershed both temporally and spatially. Using multitemporal Landsat imagery, combining segment-based and pixel-based categorization into one technique. A support vector machine methodology and the model of Markov chains were both used. It also predicted that agricultural land, built-up areas, and barren areas would continue to grow [22].

G. *Coastal zone*

This category consists of the LULC assessment of the shoreline, coastline, and surrounding area.
The study investigated and quantified the change in LULC identification and prediction in the Northern Coast Provinces of Tamil Nadu, India zone. As a post-classification change detection tool for detecting LULC modifications, a supervised classification method employing a machine learning algorithm (Random Forest) was applied [23]. Geospatial inquiry that was suggested led to the discovery of LULC changes along the shore. Considering the use of a supervised MLC to extract LULC data, coastal LULC improvements were discovered using a post-classification change detection methodology. Breakdown energy, shattering kind, and breaching zone were identified in order to detect the motion of the coastline line towards or away from the sea [24].

H. *River flow*

This category has examined studies done on rivers and areas affected by flooding. ENVI was used for LULC change detection [25]. For classification under supervision, the MLC algorithm in IDRISI17.02 was employed, and the biophysical pattern of LULCs in the sub-watershed was evaluated [26].

Table – 1
Summary of post classification techniques.

Classification methods	*Kappa Statistics*	*Overall Accuracy (%)*	*Year*	*Outcomes*	*References*
Maximum likelihood parametric	*88.21%, 83.21% and 81.68%*	*81. 68%, 82.12%, and 88.21%*	*1998, 2008, and 2018*	*Findings reveal that the urban area increased from 3.39 to 8.79 square meter between 1998 and 2018, respectively.*	*[27]*
Maximal Likelihood Algorithm	*0.8285 and 0.8656*	*92.61 and 94.75*	*2013*	*According to the results, population and water bodies have increased while vegetation has declined. Glaciers and mountains have also reduced, by 1.53% and 1.23%, respectively.*	*[28]*
ISODATA algorithm and maximum likelihood classifier	------/------	------/------	*2000 to 2017*	*The findings reveal that the volume of agricultural and aquatic bodies has dropped. Urban and slum areas as well as bare soil have shown considerable growth of 4.07 and 6.7 percent, respectively.*	*[29]*
Maximum likelihood method	*0.86, 0.82, 0.84, 0.85, 0.83, 0.85 and 0.87*	*89.01%, 86.45%, 86.73%, 87.32%, 85.23%, 88.14% and 87.51%*	*1984 to 2005*	*From 1984 to 2005, the seven temporal distribution maps of land use in the research area were obtained.*	*[30]*
ISODATA method	*0.7984, 0.7098, 0.7990 and 0.8838* *0.7569, 0.8317, 0.8356 and 0.8664*	*85% ,78%, 84% and 91%* *82% ,87%, 87% and 90%*	*1990, 2000, 2010 and 2019*	*The findings showed that the Bongo district's agricultural land experienced the largest expansion, while the woodland savannah region experienced the greatest decline.*	*[31]*
SAM algorithm	……/…….	*78%, 85.5%,95% and 100%*	*2000-2020*	*The findings showed that the Bongo district's agricultural land experienced the largest expansion, while the woodland savannah region experienced the greatest decline.*	*[32]*
Maximum likelihood classifier and Support Vector Machine (SVM)		*90%, 89%, 87%, 86%, and 84%,*	*1978, 1988, 2001, 2010, and 2020*	*The findings showed that planted forests (3966%), built-up areas (890%), agriculture (186%), and low-stocked tropical high forests (119%) had positive percentage changes (gains).*	*[33]*

Table – 2
Comparative analysis of change detection techniques.

Change Detection Methods	*Study Region*	*Best Technique*	*Results*	*References*
support vector machine (SVM)	*Urban*	*……/……*	*SVM results high overall accuracy*	*[34]*
Evaluation of four different change detection techniques	*Urban*	*ANPC*	*ANPC outperformed other PCC approaches in terms of accuracy and overall performance.*	*[35]*
Fuzzy rule-based, ISO DATA, and MLC categorization techniques were contrasted for PC CD.	*Coastline*	*Fuzzy*	*Compared to the other two classic methods, fuzzy rule-based classification produces better outcomes.*	*[36]*
Five different methods —ISO-DATA, MD, MLD, MLC, and NDWI—were used for the post classification assessment.	*lake*	*MLC*	*MLC excelled other PCC approaches in terms of accuracy and overall performance..*	*[37]*
maximum-likelihood classifier (MLC)	*Urban*	*(MLC)*	*MLC results high overall accuracy*	*[38]*
maximum likelihood method	*Urban*	*(MLC)*	*MLC results high overall accuracy*	*[39]*

III. CONCLUSION

To accurately identify the change and choose the best change detection technique, It is necessary to use multi-temporal satellite images taken with the identical detector. The analysis for the identification of relevant changes, which is a dynamic study topic, is still under development. In this paper, change detection approaches are reviewed .However, no one change detection method can be used in all situations. The majority of research investigations use post-classification procedures extensively because they produce high levels of overall accuracy. The usage of MLC for post-classification is popular. In terms of this review study, Diverse change identification approaches have been employed to assess, monitor, and pinpoint LULC variations. Despite taking certain significant elements into account, the desired study area must be observed in order to attain acceptable or high accuracy. Additionally, the literature study found that the majority of the investigations employed a post-classification technique for change. Many researcher are using various approaches when establishing change detection and then results are comparedin order to select best solution by precise assessment .The choice of an efficient change detection approach necessitates significant thought. Post-classification provides valuable information and ought to be seen as a complementary to the earlier methods. Thus, it is advised that researchers, scientists, and resource managers implement the aforementioned strategy for change approach in order to obtain notable outcomes that will aid in high a particular topic accuracy and appropriate final results to prevent additional loss. The key conclusion of this study is that no method is 100 percent accurate

DECLARATION

The authors state that they are not aware of any personal or professional conflicts that might have appeared to have influenced the study described in this work.

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