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A review on change detection method and accuracy assessment for land use land cover

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ABSTRACT

The assessment of land use land cover change is extremely important for understanding the relationship between humans and nature. The enormous changes at a regional scale and advancements in technology have encouraged researchers to gather more information. The remote sensing technology and GIS tools cooperatively have made it easier to monitor the changes in land use land cover (LULC) from past to present. This technology has unraveled the changes at the regional and global level and has also contributed tremendous benefits to the scientific community. A variety of change detection algorithms have been used in the history of remote sensing to detect changes at earth's surface and newer techniques are still in process. The data from remote sensing satellites are the primary sources that provide an opportunity to acquire information about LULC change in recent decades, which extensively use different algorithms according to the research needs. The selection of appropriate change detection method is highly recommended in every remote sensing project. This review paper begins with the traditional pre and post-classification change detection techniques related to LULC information at the regional level. Therefore, this paper evaluated the mostly used change detection method among all others to find remarkable results. Thus the review concludes the post-classification change detection method using maximum likelihood classifier (MLC) supervised classification is applicable in all cases. The comparative analysis was also performed in a selected region having multiple land features during review in which MLC results best in comparison to others. MLC is the most commonly used technique from the past till present that has achieved high accuracy in all regions comparatively to other techniques.

1. Introduction

In the course of the past three decades, remote sensing technology along with the use of GIS has provoked the importance of LULC change assessment due to more rapid and extensive changes made on earth's surface (Reid et al., 2000). In remote sensing, change detection is one of the major applications of remotely sensed data obtained from earth-orbiting satellites. Change detection is the key technique to detect LULC changes. Singh (1989) defined change detection as *"the process of identifying differences in the state of an object or phenomena by observing it at different times"*. Several studies have been conducted on the surface of earth to assess, monitor, and evaluate LULC change information coupled with the historical remotely sensed data because of repetitive coverage at short intervals (Ingram et al., 1981; Nelson, 1983; R. Anderson, 1977; A. Singh, 1984). The knowledge about the ramifications of LULC change trends is essential for obvious reasons (C. Kundalia & Ch. Chennaiah, 1978). As the world's population grows, so does the attention of the scientific and research community has aroused towards the assessment of land use land cover change (Qian et al., 2007). The increasing anthropogenic activities significantly may lead to the understanding of land use land cover change dynamics and its patterns (Halimi et al., 2017; Pasha et al., 2016). These land cover changes subsequently are essential for development (Dhinwa et al., 1992) therefore, before the development of any earth's surface, planning and management are necessary (Nations, 1992). These long term change impacts of earth's surface due to anthropogenic activities has tainted the conservation processes (Araújo et al., 2004; Sala et al., 2000; Soulé, 1991; Wessels et al., 2004) and are important to monitor using remote sensing and GIS providing useful information of past scenarios and predicts the future losses. For the assessment of these changes made on earth's surface, the selection of the most suitable method and algorithm for change detection is not easy in practice (Lu et al., 2004). The approaches which are

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widely used for change detection in remote sensing are pre-classification and post-classification. The pre-classification approach is mostly used for change and no-change, rate of change, and image enhancement. While the post-classification is mostly used for "from-to" change analysis and comparison of individually classified images (quantitatively and qualitatively). Through visual observation of high-resolution satellite images even up to some extent medium resolution satellite images can be experienced that the particular area has multiple land features (e.g: forest, urban, waterbody, agriculture, etc) or a single land feature whether anthropogenic (e.g: agriculture or urban) or natural (e.g: forest or river or low vegetation). The change detection technique for a complex study area such as multiple LULC classes at earth's surface decides which method to implement, in the past two decades till present, mostly post-classification comparison change detection method using MLC supervised classification has been implemented and proposed by (H. Abbasi, Memon, Soomro and Baloch, 2015; H. U. Abbasi, Baloch and Memon, 2011; Butt et al., 2015; Canaz et al., 2017; Choudhary et al., 2018; Dewan and Yamaguchi, 2009; Fenta et al., 2017; Fichera et al., 2017; Halimi et al., 2017; Hegazy and Kaloop, 2015; Iqbal and Khan, 2014; Kabanda and Palamuleni, 2013; Kaliraj et al., 2017; Meshesha et al., 2016; Nurwanda et al., 2016; Onur et al., 2009; Petit et al., 2010; Prabu and Dar, 2018; Rahman et al., 2012; Rawat & Kumar, 2015; Saleem et al., 2018; Samanta and Paul, 2016; Shen et al., 2011; Tripathi & Kumar, 2017; Weng, 2010; Yagoub and Kolan, 2006; Zhou et al., 2007) and some studies has implemented post-classification change detection using supervised classification minimum distance (MD), supervised classification support vector machine (SVM) and iso-data unsupervised classification (Esmail et al., 2016; Mundia and Aniya, 2007; Suribabu et al., 2012; X. Yang and Liu, 2007; Zewdie and Csaplovies, 2017) to detect changes of multiple LULC features during the study period while due to miss-pixel classification a precise classification has been implemented in some studies such as hybrid classification, decision rule-based classification, fuzzy classification and object-based classification (Adhikari et al., 2014; Chen and Wang, 2010; Hegazy and Kaloop, 2015; Kusimi, 2008; Munthali and Murayama, 2011; Samal and Gedam, 2017; Akansha Singh and Singh, 2018) to accurately extract LULC complete information and detect changes. Few studies had also applied pre-classification change detection methods for feature extraction to detect pixel by pixel change and transformation algorithm to reduce noise data for better classification and extract much more or useful information for the particular or single LULC feature in the past decades, for example, normalized difference vegetation index (NDVI) was implemented by (Zhou et al., 2011) reported the natural and human-induced changes are comparatively low than changes in vegetation while (Jung and Chang, 2015) to identify change and no-change using harmonic analysis and (Ghobadi et al., 2013) detected land surface temperature (LST) through NDVI because LST and NDVI have strong inverse correlation also concluded by (Olorunfemi et al., 2018) during identification of temperature regime due to urbanization. (Xiaolu and Bo, 2011) proposed change vector analysis (CVA) to detect change and direction of change and (Zanchetta et al., 2016) monitored desertification by the combination of two methods CVA and tasseled cap transformation (TCT) to detect changes while (Haijiang et al., 2008) also monitored sandy desertification by applying TCT to enhance land surface before classification.

The main purpose of this paper is to review and focus the type of earth's surface regions in the context of LULC classes to define the suitable change detection method for extracting better LULC change information whether by implementing pre-classification change detection technique or post-classification comparison technique of individually classified multi-temporal multispectral medium resolution remotely sensed satellite data because it is freely and easily available such as Landsat mission in comparison of high-resolution satellite data such as SPOT, IKONOS, QUICK BIRD, etc., which is much more costly for academic and individual researchers. Due to the importance of monitoring change in earth's surface features, there is a gigantic need for scientific research for the evaluation of change detection techniques which is currently an active topic and new techniques are continuously developing.

2. A review of change detection techniques

In order to the selection of appropriate change detection methods, this review research has focused the evaluation of LULC features of different landscape regions to describe which change detection method is better to execute. Therefore in this section a diversity of change detection methods has been reviewed according to earth's land surface and has been categorized into eight different regions which are: 1) Vegetation, 2) Urbanization, 3) Delta Region, 4) Mountainous Region, 5) River Flow, 6) Coastal Zone, 7) Desertification, and 8) Watershed.

Most of the studies were trying to answer the reasons of what drives the changes in LULC of the region (Geist & Eric F. Lambin, 2001; Kanianska et al., 2014; Lambin et al., 2001) and what are the impacts of these changes on both environmental and socio-economic conditions of a given region, (S. Ayanlade, 2016a; S. Ayanlade and Proske, 2016; Drescher et al., 2016; Lawler et al., 2014; Popp et al., 2017). To effectively answer these questions, several change detection methods have been developed to assess and monitor LULC change and its impacts on changing climatic conditions. Furthermore, the change detection methods discussed in this review are concerning above categorized earth's regions.

2.1. Vegetation

A variety of change detection methods has been reviewed in this category. This category includes forest areas, agricultural areas, and large-scale plantation schemes such as orchards.

(Zhou et al., 2007) detected changes using the post-classification change detection method in the fragile ecosystem of arid environment China, by performing a supervised classification MLC. This study results during the study period threefold increase of croplands and achieved an overall accuracy of 85–90% with a kappa coefficient of 0.66–0.78 from individual classification (Kusimi, 2008). assessed LULC change in the Wassa West district of Ghana. Supervised classification MLC was used to perform the post-classification change detection technique after an un-supervised iso-data clustering technique which helps to identify landscape features. This study results in the reduction of primary forest which covered 88% of the study area were reduced to 69% (almost 19% loss) during the study period. (Prakash and Gupta, 2010) proposed comparative change detection analysis of image differencing, image ratioing, and NDVI differencing during land-use mapping in a coal mining area of Jharia Coal Field, India. The different change detection methods were applied to compare change results concluded that no single technique is sufficient for evaluating land-use change information of all land types. Because each method has its own merits in detecting the land-use change in the study area (Petit et al., 2010). quantified the LULC changes and future prediction of LULC changes in the region of Lusitu, southern province of Zambia. Multispectral spot satellite imagery was used to observe land cover information using post-classification. This study results in a huge expansion in the agriculture sector after implementing the MLC. Markov based model was used to predict future land cover changes (Zhou et al., 2011). reported the natural and human-induced impact on arid environment Yuli county, China. Categorical changes of LULC were identified using supervised classification. And quantitative changes were identified using NDVI resulting in no improvement or land degradation by human impacts. This study reveals that human impact is comparatively low than the natural impact on vegetation (Munthali and Murayama, 2011). estimated LULC change detection of Dzalanyama forest reserve with the help of fuzzy classification and predicted further changes in the future through markov chain analysis. The results showed that the deforestation was mainly due to anthropogenic activities and no recent signs of abating if the situation is left unattended (H. U. Abbasi et al., 2011). analyzed decadal LULC change of riverine forest of Sindh, Pakistan using landsat satellite imagery. Supervised classification MLC was applied to detect changes quantitatively by the post-classification comparison technique. This study revealed that continuous loss of sub-tropical forest was mainly due to anthropogenic activities that drive riverine forest to dry barren land (Vorovencii, 2014). compared change detection techniques and detected LULC changes in south-east Transilvania, Romania. Image differencing, NDVI differencing, principal component analysis (PCA), and post-classification change detection techniques were used to detect LULC changes. In the comparison of four change detection methods, the results reveal that NDVI differencing achieved a high overall accuracy of 83.80% and kappa value 0.6323. The post-classification results in 83.20% overall accuracy and 0.6206 kappa. While the PC2 difference and TM band 4 difference achieve overall accuracy of 81.60% and 79.40 and kappa value of 0.5759 and 0.5243 (Adhikari et al., 2014). examines forest loss and recovery of Bannerghatta national park, India. A hybrid classification technique and continuous NDVI was applied to detect changes. Initially, unsupervised classification iso-data were used to identify various land covers. After unsupervised classification, supervised classification Gaussian MLC was performed to quantify land cover types. A post-classification comparison results reforestation during the study period, while continuous NDVI values range from -1 to $+1$ with values closer to $+1$ considered to correspond to a higher amount of photosynthetically active green biomass (Tucker, 1979). Image differencing was performed for each standardized NDVI pair of the study period which also showed an increasing trend (H. Abbasi et al., 2015). reported rapid loss of riverine forest of Nawabshah and Hyderabad division. Supervised classification MLC was applied to identify quantitative forest cover change from 1979 to 2010 using the post-classification comparison technique. This study reveals a huge change in a sub-tropical forest which results in decreasing change from 42.67% to 0.722% during the study period (Minu and Shetty, 2015). did a comparative analysis of Image Differencing, Image Ratioing, CVA, PCA, and TCT to detect changes in the agricultural land area of Yagachi of Belur in Karnataka, India. The results were compared with the supervised classification MLC by post-classification change detection technique to assess the effectiveness and accuracy. This study results showed that the image differencing of band 4 give accuracy more than 65% from other bands, image ratioing gave poor results and PCA gave change percentages in each band while TCT achieved good overall accuracy and kappa value. Among all five change detection techniques, CVA was found to be the most appropriate technique and TCT standing next to CVA (Jung and Chang, 2015). classified NDVI-based land cover of a long term cumulative historical change map. Moderate resolution imaging spectrometer (MODIS) NDVI multi-temporal long-term data were used to analyze the periodic change map. Initially, noise data were identified using differentiation to apply harmonic on noise reduced reconstructed NDVI data streams and harmonic components were generated. Mahalanobis distance (MLD) method was applied to harmonic components to classify change and no-change resulting value zero for change and value 1 for no-change. The classification results indicate that the change in the temporal profile can be detected by the proposed algorithm based on applied harmonic analysis (Nurwanda et al., 2016). determined LULC changes and analyzed landscape fragmentation in Batanghari Regency, Jambi Province. The MLC was applied to detect forest cover during the study by using a post-classification comparison. The results reveal forest cover declining from 63.6% to 20.6%. (Pasha et al., 2016) proposed LULC changes during the study period and also monitored hot and cold spots by optimized hotspot analysis tools in ArcGIS software. This study supported the increase of mangrove forestation and reveals that during the study period the total area of mangroves increased from 140 km^2 to 700 km^2 and the decline in mangroves 21.4 km^2 was due to increase in built-up, saltpans (Zewdie and Csaplovies, 2017). examined LULC changes of semi-arid region Kafta Humera, Ethiopia using multi-temporal landsat satellite imagery. The post-classification change detection method was performed in this study to identify land cover changes using supervised classification SVM. The results quantify the dynamics of land cover change with an elevation below 1000 m with a loss of 74% of woodlands during the study period because of increasing anthropogenic activities like overharvesting of trees, settlement expansion, and agricultural land expansion (Haque and Basak, 2017). evaluated the typical landscape changes from past to present. In this study, both pre-classification and post-classification change detection approaches were used to assess and evaluate landscape changes during the study time. In the pre-classification approach NDVI, NDWI, and CVA methods were executed among them NDVI and NDWI helped to accurately identify the vegetation and water bodies while CVA described the magnitude and direction of the land cover change. In the post-classification approach supervised classification MLC was used to quantify the amount of change in each type. The results showed an increasing trend in shallow water and settlement while the decreasing trend in deep water and vegetation. This study concludes that 40% of the study area had been changed due to anthropogenic activities.

2.2. Urbanization

This category is based on the researches made upon cities and urban sprawl.

(K Ridd and Liu, 1998) compared four change detection algorithms in an urban environment of Salt Lake City metropolitan of Utah, United States. Image differencing, image regression, TCT, and CHI-square transformation were used to identify the best change detection method. The study was categorized into 7 categories which are: (1) Construction site to new residential (2) new residential to vegetated residential (3) Farmland to construction site (4) Farmland to industrial/commercial (5) Dry farm to green farm (6) Green farm to dry farm (7) Soil/Gravel tonal change. Among these 7 categories, this study concluded that none of the above mention algorithms has defined change in all 7 categories (Mundia and Aniya, 2007). analyzed LULC changes, dynamics of unplanned urbanization, and urban sprawl causes gigantic loss of forest of Nairobi, Kenya. The post-classification change detection method was implemented using an unsupervised classification iso-data algorithm to assess the LULC change of individually classified images. The overall accuracy and kappa indices above 80% (Deng et al., 2008). presented PCA and hybrid classification of multi-temporal and multi-sensor satellite imagery to detect land use changes in an urban environment of Hangzhou city, China. The results revealed that PCA based change detection yielded better accuracy rather than post-classification based approach (Dewan and Yamaguchi, 2009). detected LULC change in Dhaka metropolitan city, Bangladesh. Supervised classification MLC before the post-classification change detection technique was used. The results revealed rapid and gigantic urbanization during the study period (Onur et al., 2009). detected LULC changes during the study of Kemer, Turkey. LULC classes were determined by visual interpretation, 3d aerial photographs, and unsupervised classification. Finally, supervised classification MLC was used to extract LULC information and was verified by the Co-ordination of Information on the Environment (CORINE). The post-classification change detection technique was performed in the study results destruction of forest and agriculture, while the increase in urban settlement and inland water. This huge change from a little village to urban fabric was mainly due to tourism and attractive summer resorts (Weng, 2010). evaluated urban expansion and its impact on surface temperature in the Zhujiang delta, China. Post-classification change detection was proposed to identify qualitative and quantitative change. Supervised classification MLC was used for urban expansion. NDVI was calculated to assess surface temperature because NDVI has been found the best/good indicator of surface radiance temperature (Nemani and Running, 1989; Gallo et al., 1993; Gillies and Carlson, 1995; Lo et al., 1997) (Shen et al., 2011). analyzed urban LULC changes of Beijing, China during the study period using supervised classification MLC to extract quantitative LULC information. The post-classification change detection technique was applied to detect LULC changes results reduction of water due to climate, hydrology, and urbanization during the study period (Xiaolu and Bo, 2011). proposed change and direction of change using CVA and MD supervised classification. Initially CVA was used to detect change and no-change pixel while MD supervised classification was performed to define direction of change. This study concludes that CVA results 95.99% accuracy of change detection after determining a proper threshold by dichotomy (Kamh et al., 2011). evaluated urban land cover change in the Hurghada, Egypt. Five different change detection methods image ratioing, image differencing, image overlay, PCA, and post-classification comparison technique using supervised classification MLC was used to extract LULC change information. Among the proposed methods post-classification change detection method was found to be the most appropriate and accurate method (Varshney et al., 2012). has proposed a new algorithm to detect LULC changes in Dehradun city, the capital of a newly formed state of India. Median change vector analysis (MCVA) to detect a multiclass change and assessed accuracy by comparing it with improved change vector analysis (ICVA). ICVA was promoted as an effective algorithm for multiclass change detection rather than conventional CVA. The new algorithm MCVA was proposed to compare with ICVA and post-classification change detection technique to assess the performance of all three techniques. The thematic overall accuracy of MCVA was 64% while ICVA was 60% and post-classification was 56% (Rahman et al., 2012). assessed LULC changes during the study period by acquiring topographical sheets provided by a survey of India and satellite data. Supervised classification MLC was used to evaluate LULC change information and post-classification change detection technique to detect “from-to” quantitative change and achieved acceptable overall and kappa values of the classified maps (Suribabu et al., 2012). focused urbanization of Tiruchirappalli city, India to detect LULC changes by post-classification comparison change detection technique. Supervised classification MD was applied to every individual image after the identification of LULC classes using unsupervised classification results in a huge urban expansion during the study period (Liu and Weng, 2013). analyzed urban-induced LULC changes and landscape diversity using landscape metrics of each LULC class in Indianapolis city, capital of Indiana, USA. Landsat and ASTER satellite data was to identify LULC types using unsupervised classification. The study results showed that ASTER classified images achieved high overall accuracy and kappa value than landsat classified images. Landscape metrics change detection results revealed that urbanization was mostly increasing type among all other LULC types (Du et al., 2014). proposed sub-pixel change detection approach in order to analyze urban area using non-linear Back Propagation Neural Network (BPNN) and V–I–S model. The results were compared with traditional CVA and PCA showed that the overall accuracy and kappa statistics were much better than the CVA and PCA (Iqbal and Khan, 2014). proposed LULC change analysis and erosion risk mapping of Azad Jammu and Kashmir. Supervised classification MLC was performed after un-supervised classification to identify LULC types. ASTER DEM was also used to extract topographic information. The erosion risk map was generated by assigning weight to the thematic layers using weighted overlay analysis, and the slope gradient percentage was calculated from ASTER DEM to classify erosion risk according to the slope. The post-classification comparison technique was used to detect LULC change results in a decreasing trend in the forest and low vegetation, while the increasing trend in built-up and bare land. The results of the erosion risk map showed 59% of the area lies under low risk while 12% of the area lies under very high risk. Whereas 24% and 5% of the areas were under medium and high risk (X. t. Yang, Liu and Gao, 2015). proposed object-based change detection to assess the land cover change of an urban fringe area in north Beijing, China. This study was mainly composed of four stages: multi-temporal segmentation, selection of the optimal segmentation scale, changed object extraction, and accuracy assessment. Initially, the selection of the best combination of change indicators by Optimum Index Factor and Chi-square transformation was applied to determine change objects from unchanged ones. This research study proves that the land cover object-based change detection method is efficient to detect changes that result in changed and unchanged object extraction with an overall accuracy of 93.9% and kappa of 0.824 (Hegazy and Kaloop, 2015). proposed land-use change detection and monitored urban growth during the study of Daqahlia, Egypt. Initially, unsupervised classification was performed to understand the distribution of the pixels using the iso-data clustering algorithm. After unsupervised classification, supervised classification was performed using MLC to identify the land cover type and generated the LULC map successfully. LULC change analysis was detected using the post-classification change detection technique. The Markov chain model was also applied to predict future LULC changes. This study results continuously increasing trend in urbanization and will increase by 16% more in the future (Lal and Margret Anouncia, 2015). monitored LULC change using semi-supervised classification applied on the Dead Sea located in the middle east in between Israel and Jordon. Enhanced constrained K-means (ECKM) were analyzed quantitatively and qualitatively in comparison with Adaptative K-means, Fuzzy K-means, and K-means using post-classification change detection technique. The results seem to be far better of the proposed approach ECKM than other methods. The proposed approach identified pixel more accurately along with less chance of misclassification (Fichera et al., 2017). detected LULC change during the study of Avellino, southern Italy. Supervised classification MLC was applied to identify LULC information due to a disastrous earthquake in between of the study period. The post-classification change detection technique was applied to detect “from-to” quantitative change. The results showed expansion in the urban land cover, while woodland and grassland have shown a relatively lower change rate (Fenta et al., 2017). evaluated the dynamics and spatial pattern of northern Ethiopia, Mekelle city. Supervised classification MLC was used to produce LULC changes which were detected by the post-classification change detection method. The area increased six-fold and about 88% gain in the built-up area was from the conversion of agriculture farms. The results achieved overall accuracy and kappa statistics between 80% and 90% and 0.8 to 0.88 (Samal and Gedam, 2017). monitored LULC changes due to urbanization in Pune, India. An object-based image analysis approach was performed for better classification. This study reveals that during the study duration the built-up area has expanded massively. The total change of 288 km^2 (+181.1%) occurred during the study period, which is highly irreversible (Canaz et al., 2017). monitored LULC changes in Istanbul, Turkey. MLC was used to detect changes in manmade structures and vegetation. This study concludes that using the post-classification change detection method results showed an increasing trend in manmade structures from 4.19% to 17.26%, while the decrease in vegetation from 59.54% to 38.75% which is mainly due to rapid population growth and urbanization. This research also explains the land transformation from natural environment areas to buildings and industries (Halimi et al., 2017). proposed LULC changes of Kan Basin, Iran using supervised classification MLC. The post-classification comparison technique was used to identify LULC change dynamics, which results in an increase of built-up and pasture, decrease in garden and bare land, while the water area completely vanished (Saleem et al., 2018). proposed LULC quantitative change analysis and long term LULC mapping of Kurdistan, Iraq. Supervised classification MLC was applied to evaluate “from-to” LULC change after un-supervised classification. Finally, the post-classification technique was used to detect LULC changes during the study period (Choudhary et al., 2018). assessed environmental vulnerability using the landscape pattern of Astrakhan city, Russia. Supervised classification MLC was used to perform LULC change using the post-classification comparison technique. The environmental vulnerability was identified, assessed, and classified by generating thematic maps that give weight to different landscapes based on their sensitivity. This study reveals that among the total area, 54.62% has moderate vulnerability while the extreme vulnerability is 0.15% and the area under low vulnerability is 5.62% Akansha Singh and Singh (2018) proposed a novel based change detection method to identify the change and no change using spectral change index and similarity index. These two indices were computed using CVA and kullback leibler distance (KLD). The change information was gathered by combining these two indices using the wavelet fusion rule to obtain complete change information. Finally, a change map was obtained by classifying the fused image into changed and unchanged classes using Neuro-Fuzzy Classifier. The proposed method results in high overall accuracy in comparison to CVA and KLD. Urban area, natural landscape, or even after a natural disaster when the image acquisition conditions are extremely different the proposed method will give good results (Prabu and Dar, 2018). analyzed LULC change and urban expansion in Coimbatore city, Tamil Nadu, India. Supervised classification MLC was used to perform the post-classification change detection method. The results showed most of the LULC classes were converted to the urban area during the study period (Zadbagher et al., 2018). analyzed LULC change and proposed a mathematical modeling approach to predict future LULC changes. The object-based classification was applied to detect LULC changes using a post-classification change detection method. The Cellular Automata and Markov Chain (CA-MC) model were applied to predict future changes (Patra et al., 2018). assessed the impacts of urbanization on LULC change and groundwater depth level. K-mean unsupervised classification approach was used to assess LULC classes. And Inverse Distance Weighting (IDW) interpolation method was applied for the spatial distribution of temperature, rainfall, and groundwater level analysis. This study reveals that during the study period huge urban expansion up to 58% causes loss in vegetation, biodiversity, wetlands, and a rise in groundwater depth, temperature, and low rainfall in the area.

2.3. *Delta region*

The review of estuaries and delta regions has been discussed in this section.

(X. Yang and Liu, 2007) investigates coastal LULC changes of the Pensacola estuarine ecosystem that has been disturbed due to significant low urban growth. Also, the population has shown an increasing trend during the study period which destroys the watershed. Unsupervised classification iso-data clustering was applied. The post-classification change detection method has made it possible for the production of a single theme change map, which emphasizes spatial dynamics (Berberoglu and Akin, 2009). compared image differencing, image ratioing, image regression, and CVA change detection methods to assess their effectiveness for detecting LULC changes in the Cukurova deltas, south-east Mediterranean coastal region of Turkey. An object-based supervised classification was used as a cross-classification to determine 'from-to' change and estimates the accuracy of four change detection methods. Among all four-change detection methods, CVA was found to be the most appropriate method for change assessment in Mediterranean LULC.

2.4. *Mountainous region*

The research study conducted on high and low steep mountainous and hilly region is reviewed here.

(Chen and Wang, 2010) detected LULC changes at three gorges DAM area along the Yangtze river, China. A decision rule-based classification method and post-classification techniques were performed. Initially, the MLC was applied and then the GreyTone spatial-Dependency method was applied for miss-classification. Images were re-classified including ASTER DEM data, resulted in a 4–5% increase in the classification accuracy in comparison to the traditional MLC method. This study revealed that the major LULC changes occurred between 0 and 35° slopes that causes loss in natural vegetation (Rawat & Kumar, 2015). monitored LULC changes in Hawalbagh block district Almora, India. Supervised classification MLC was used before the post-classification change detection technique to identify the type of land and the changes that occurred during the study period. The results showed a positive change in vegetation due to afforestation in the region and increasing trend in built-up, while a decrease in barren land and agriculture (Tripathi & Kumar, 2017). quantifies the LULC changes in the Almora district Uttarakhand, India Himalayas region. Supervised classification MLC was used to detect LULC changes during the study period. The results revealed a decreasing trend in forest class than other LULC classes. The overall classification accuracy lies in between 85 and 90% while kappa statistics value ranges 0.75–0.79.

2.5. *River flow*

The researches made on rivers and flood affected areas has been reviewed in this category.

(Sharma et al., 2011) assessed pre and post-flooding LULC change of three districts of Gujrat state, India. Three different classification approaches iso-data, MLC, and fuzzy rule base were applied to extract LULC information. The post-classification change detection method was used to detect "from-to" quantitative change analysis during the study period. The Kappa statistics values of all three classifications were computed and compared. The comparison of kappa values showed that un-supervised classification ISO-DATA achieved 0.78, supervised classification MLC achieved 0.84, and the Fuzzy rule base classification achieved 0.87 because fuzzy rule classification gave better separation of LULC classes (Kabanda and Palamuleni, 2013). determined the hydrological impacts using remote sensing and GIS. Landsat satellite images were used to perform classification and post-classification change detection. MLC supervised classification technique was applied to identify different LULC classes. The LULC classes were verified using transformed divergence value. The value of 1500 or greater shows the successful separation of classes. The LULC changes showed a decreasing trend in vegetation cover and an increasing trend in barren land due to changing flow regimes in Harts catchment.

2.6. *Coastal zone*

The LULC assessment of coastline and seashore areas and its surroundings falls under this category.

(Yagoub and Kolan, 2006) evaluated and quantified the LULC change of the Abu Dhabi coastal zone during the study period. Supervised classification was applied for a post-classification change detection method to detect LULC changes (Muttitanon and Tripathi, 2008). illustrated LULC changes of Ban Don Bay Thailand using different change detection methods. Supervised classification MLC was used to identify LULC classes. Change detection was observed by proposing image differencing, NDVI differencing, and NDVI-composite classification to observe change and no-change. Image differencing and NDVI differencing was quite similar (10.84–10.89), while NDVI composite shows a quite clear map of change and no-change (Esmail et al., 2016). monitored LULC changes during the study of Damietta promontory, Egypt. The post-classification change detection technique was applied after the supervised classification SVM technique for the identification of LULC changes. The results revealed that 3.03% of coastal area has been eroded at the promontory similarly urban settlement also increased during the study period (Samanta and Paul, 2016). proposed geospatial analysis and detected coastal LULC changes. Supervised classification MLC was used to extract LULC information and a post-classification change detection method was applied to detect coastal LULC changes. The breaking zone, breaking energy, and breaking type was calculated to identify the shifting of the coastal line towards or backward the sea (Hoover et al., 2017). combined participatory data and remote sensing (RS) satellite data to assess swidden LULC changes. This study concludes that the classification of swidden LULC change is difficult and more prone to mixed pixels by alone RS data. The combined assessment of RS

Table 1
Summary of the post-classification technique.

References	Classification Technique	Overall Accuracy (%)	Kappa Statistics	Year	Result
Yagoub & Kolan (2006)	Minimum Distance	88.2649	0.8528	1972–2000	Agriculture land was decreased and barren land was increased during the study period.
Zhou et al. (2007)	MLC	85–90	0.66–0.78		The study period threefold increase of croplands
(X. Yang and Liu, 2007)	ISO-DATA	92.40, 94.53, and 94.13	0.91, 0.93, and 0.93	1989, 1996, and 2002	Growing suburbanization at Pensacola bay causes loss in evergreen forest
Mundia & Aniya (2007)	ISODATA	90, 91, and 87	0.86, 0.85, and 0.81	1976, 1988, and 2000	Loss of forest due to urban area increased by 47 km^2
Haijiang et al. (2008)	MLC	87.33, 89.25, and 92.34	–/–	1987, 2000, and 2006	Sandy desertification and land degradation in mainly due to human induced processes but can be controlled through government policies
Dewan & Yamaguchi (2009)	MLC	85.6%, 86.4%, 90.4, 90, and 88.2	82.7%, 83.7%, 88.5%, 87.9%, and 85.6%	1975–2005	The research revealed rapid urban growth from 11% to 334%
Onur et al. (2009)	MLC	89.20, 93.60, 89.20, and 90.80	0.87, 0.92, 0.87, and 0.89	1975–2003	Urban growth results destruction in agriculture and forest
Chen & Wang (2010)	Decision rule-based Classification	73.4, 76.9, and 89.5	–/–	1987, 2002, and 2006	The LULC changes not only occur on slope at 35 °C but also at slope steeper than 35 °C
Petit et al. (2010)	MLC	83%	80%		
Weng (2010)	MLC	90.57 and 85.43	0.89 and 0.83	1989–1997	Urban expansion raised surface radiant temperature to 13.01 k
Shen et al. (2011)	MLC	–/–	–/–	1992–2009	Urbanization causes transformation of agricultural land into urban land
Zhou et al. (2011)	MLC	–/–	–/–	1973–2000	Human impact is comparatively low than natural impact on vegetation
Munthali & Murayama (2011)	Fuzzy Classification	81, 78, and 79	0.63, 0.58, and 0.72	1990–2008	Deforestation was mainly due to anthropogenic activities
(H. U. Abbasi et al., 2011)	MLC	99.96, 99.9, 99.53, 99.96, 99.93, and 99.68	0.99, 0.99, 0.99, 0.99, 0.99, and 0.99	1979–2009	Deforestation due to anthropogenic activities
Rahman et al. (2012)	MLC	74	71	1972–2003	Urban expansion leads to unplanned development
Suribabu et al. (2012)	Minimum Distance	–/–	–/–	1989–2010	Increasing urban development from 9.33 to 25.67 km^2 leads to loss of greenness.
Liu & Weng (2013)	Unsupervised Classification	84, 83.67, 87, and 89	0.81, 0.80, 0.84, and 0.86	1989–2006	Four landscape metrics were applied to quantify the LULC patterns and detect changes
Kabanda & Palamuleni (2013)	MLC	89, 86.67, and 88.3	–/–	1990, 2005, and 2008	The LULC changes showed decreasing trend in vegetation cover and increasing trend in barren land due to changing flow regimes in Harts catchment.
Du et al. (2014)	Sub-pixel based change detection approach	89.86	0.77	2005–2007	Sub-pixel based CD method was applied in comparison to traditional CVA and PCA.
Iqbal & Khan (2014)	MLC	89 and 86	86 and 82%	1998–2009	Increasing trend in built-up results in vegetation and forest loss
Hegazy & Kaloop (2015)	MLC	86.67, 84, and 85.2	–/–	1985, 2000, and 2010	Markov chain analysis was used for future prediction of further urbanization impacts
(H. Abbasi et al., 2015)	MLC	99, 99, 99, 100, 100, and 99	0.99, 0.99, 0.99, 1.0, 1.0, and 0.99	1979–2009	Loss of forest in Hyderabad division was about 89%
Rawat & Kumar (2015)	MLC	90.29 and 90.13	0.823 and 0.912	1990–2010	Human settlement and forest vegetation has been increased in this rough terrain region during study period.
Butt et al. (2015)	MLC	95.32 and 95.13	0.9237 and 0.9070	1992–2012	Unplanned changes occurred due to anthropogenic activities resulting increasing trend of agriculture and settlement while decreasing trend in water and vegetation
Samanta & Paul (2016)	MLC	85, 86, 88, and 91	0.80, 0.84, 0.86, and 0.88	1973–2002	LULC proves that changes in coastal zone are mainly due to population pressure.
Esmail et al. (2016)	SVM	0.97–1.0	–/–	1987–2015	Sew water and urban area were increased at Nile delta coastal zone.
Nurwanda et al. (2016)	MLC	86.60, 98.98, 91.24, and 97.57	0.6, 0.98, 0.88, and 0.96	1988–2014	Research showed increasing trend in palm oil plantation while decreasing trend in forest of Batanghari from 63.6% to 20.6% during study period
Pasha et al. (2016)	Land use/cover classification	92.64	0.89	1977–2015	Research revealed afforestation during the study period
Tripathi & Kumar (2017)	MLC	89.22 and 87.72	0.7783 and 0.7633	1990–2005	The study concludes, using RS and GIS a sustainable planning in the study area can easily be implemented.
Kaliraj et al. (2017)	MLC	89.61	0.89	2000 and 2011	Coastal land was converted to urban settlement because of anthropogenic activities which results shoreline erosion and morphological changes
Zewdie & Csaplovies (2017)	SVM	84.4, 92.0, 90.6, and 92.7	0.78, 0.90, 0.88, and 0.91	1972–2010	Anthropogenic activities, such as agriculture and settlements are severely diminishing the natural ecosystem
Haque & Basak (2017)	MLC	73.91, 80.49, 91.30, and 89.13	0.65, 0.72, 0.88, and 0.85	1990–2010	Pre and post classification were applied and among both post classification gave best results

(*continued on next page*)

Table 1 (*continued*)

References	Classification Technique	Overall Accuracy (%)	Kappa Statistics	Year	Result
Fichera et al. (2017)	MLC	86.72, 82.42, 83.20, and 97.70	0.7478, 0.6863, 0.7060, and 0.9285	1954–2004	Urban expansion has been increased from 1.6% of the study area to 9.1%
Fenta et al. (2017)	MLC	86, 85, 87, and 89	0.81, 0.80, 0.82, and 0.86	1984, 1994, 2004, and 2014	Increasing built-up gave loss to other land cover types
Canaz et al. (2017)	MLC	79–88%	0.6830–0.8451	1986–2015	Rapid growth urbanization trends loss in vegetation
Halimi et al. (2017)	MLC	86–89%	0.84 and 0.85	2000–2016	Identifying the changes occurred during the time period
Saleem et al. (2018)	MLC	79–89%	0.72–0.86	1972–2014	Rapid growth in economy, population and urbanization
Choudhary et al. (2018)	MLC	–/–	–/–	2000, 2007, and 2015	This research experiences LULC and vulnerability changes.
Prabu & Dar (2018)	MLC	–/–	87.60 and 86.15%	2003 and 2014	The city has experienced rapid modifications LULC patterns due to human settlement
Zadbagher et al. (2018)	Object based classification	–/–	77%	1995–2016	Cellular automata markov chain model was used to predict future loss

and participatory data will be more accurate to define swidden LULC change (Kaliraj et al., 2017). estimated decadal changes and their transformations of LULC features of Kanyakumari Coast, India. The post-classification change detection was used to detect LULC changes after applying supervised classification MLC. This study concludes that most coastal lands were converted to an urban settlement because of anthropogenic activities that result in shoreline erosion and morphological changes (Hossen et al., 2018). assessed and predicted future LULC changes in Manzala Lake, the largest coastal lake in Egypt. Five different classification techniques were used in this study unsupervised iso-data clustering, MD, MLD, MLC, and NDWI among which MLC was selected to detect LULC changes because it achieves high overall accuracy and kappa value in comparison to other techniques. The linear regression model was selected to predict future LULC changes.

2.7. Desertification

The drought and dry land areas falls under this category are reviewed.

(Haijiang et al., 2008) monitored sandy desertification of Otinday sandy land. The TCT technique was applied to images before the post-classification change detection method. MLC was used to classify the study area. This study reveals that sandy desertification and land degradation is mainly due to human-induced processes (Zanchetta et al., 2016). monitored desertification of Azraq Oasis, Jordan. With the combination of two methods CVA and TCT for detecting of changes. The result showed expansion in bare soil which accounts for more than 80% of the total change.

2.8. Watershed

The researches on watershed are reviewed in this category.

(Butt et al., 2015) proposed LULC mapping and change detection of Simly watershed Islamabad, Pakistan. MLC supervised classification was to extract LULC features and a post-classification change detection method was applied to detect LULC changes. This study concludes that unplanned changes occurred due to anthropogenic activities resulting in an increasing trend of agriculture and settlement while decreasing trend in water and vegetation (Meshesha et al., 2016). identified LULC change dynamics in the Beressa watershed, Ethiopia. Satellite images were classified using supervised classification and post-classification change detection techniques were applied to optimize LULC change analysis. The results showed drastic expansion of farmland and settlement land while increasing forest cover due to government incentives provided to households and communities.

3. Analysis of literature review

In the previous section, eight different regions were reviewed along with a variety of change detection techniques applied. This section will evaluate the most commonly used change detection method applied to many of the research studies in the past two decades until the present. The post-classification change detection using MLC supervised classification has been implemented the most and proposed by (H. Abbasi et al., 2015; H. U. Abbasi et al., 2011; Butt et al., 2015; Canaz et al., 2017; Choudhary et al., 2018; Dewan and Yamaguchi, 2009; Fenta et al., 2017; Fichera et al., 2017; Halimi et al., 2017; Hegazy and Kaloop, 2015; Iqbal and Khan, 2014; Kabanda and Palamuleni, 2013; Kaliraj et al., 2017; Meshesha et al., 2016; Nurwanda et al., 2016; Onur et al., 2009; Petit et al., 2010; Prabu and Dar, 2018; Rahman et al., 2012; Rawat & Kumar, 2015; Saleem et al., 2018; Samanta and Paul, 2016; Shen et al., 2011; Tripathi & Kumar, 2017; Weng, 2010; Yagoub and Kolan, 2006; Zhou et al., 2007). While some of the studies have implemented post-classification change detection using supervised classification MD, SVM, and iso-data unsupervised classification (Esmail et al., 2016; Mundia and Aniya, 2007; Suribabu et al., 2012; X. Yang and Liu, 2007; Zewdie and Csaplovies, 2017) to detect changes of multiple LULC features during the study period. Due to the miss-pixel classification, a precise classification technique has been implemented in some studies such as hybrid classification, decision rule-based classification, fuzzy classification, and object-based classification used by Adhikari et al. (2014); Chen and Wang (2010); Hegazy and Kaloop (2015); Kusimi (2008); Munthali and Murayama (2011); Samal and Gedam (2017); Akansha Singh and Singh (2018) to accurately extract LULC complete information and detect changes. A summary of the accuracy assessment for post-classification change detection methods with different classification techniques results obtained is given in Table 1.

Few studies had also applied pre-classification change detection technique for a single land feature to detect the changes and extract useful information, for example, NDVI was implemented by Zhou et al. (2011) reported the natural and human-induced changes are comparatively low than changes in vegetation (Jung and Chang, 2015). identified change and no-change using harmonic analysis (Ghobadi et al., 2013). detected land surface temperature (LST) through NDVI because LST and NDVI has strong inverse correlation which was also concluded by Olorunfemi et al. (2018) during identification of temperature regime due to urbanization (Xiaolu and Bo, 2011). proposed CVA to detect change and direction of change (Zanchetta et al., 2016). monitored desertification by combination of two methods CVA and TCT to detect changes (Haijiang et al., 2008). monitored sandy desertification by applying TCT to enhance land surface before classification.

The comparative analysis of change detection methods is adapted to justify the best method through thematic accuracy assessment results as

Table 2
Comparative analysis of change detection techniques.

References	Change Detection Methods	Best Technique	Study Region	Results
K Ridd & Liu (1998)	Comparison between four change detection methods	–/–		None of the algorithm was superior to other
Deng et al. (2008)	Comparison between post-classification and PCA-based post-classification	MLC		PCA-based post-classification results more accuracy in comparison to just post-classification
Berberoglu & Akin (2009)	Four change detection methods was applied	CVA	Mediterranean	CVA results high overall accuracy
Prakash & Gupta (2010)	Image differencing, image ratioing, and NDVI	–/–	Coal Field	Concluded that no single technique is sufficient for evaluating land-use change because each method has its own merits in detecting land-use change
Sharma et al. (2011)	Three classification techniques fuzzy rule-based, ISO-DATA and MLC classification were compared for PC CD.	Fuzzy	Coastline	Fuzzy rule-based classification results better than other two traditional methods
Kamh et al. (2011)	Comparison between Image differencing, Image ratioing, image overlay, multidate PCA and Post-classification	MLC	Urban	Post-classification using MLC results high accuracy
Varshney et al. (2012)	New developed MCVA was compared with ICVA and MD to mean classification rule	MCVA	–/–	MCVA achieved high accuracy
Lal & Margret Anouncia (2015)	Semi-supervised classification was used. Comparing results of ECKM, AKM, and FCM techniques using PCC CD method.	ECKM	–/–	The proposed technique ECKM provided better results in comparison to other techniques
Hossen et al. (2018)	Five techniques where applied for post-classification comparison ISO-DATA, MD, MLD, MLC and NDWI	MLC	Lake	MLC achieved high overall and kappa accuracy than other techniques for PCC.

(Prakash and Gupta, 2010) proposed comparative change detection analysis of image differencing, image ratioing, and NDVI differencing while land-use mapping in a coal mining area of Jharia coal field, India concluded that no single technique is sufficient for evaluating land-use change information of all land types because each method has its own merits in detecting a land-use change in the study area (K Ridd and Liu, 1998). compared four change detection algorithms in an urban environment of Salt Lake city metropolitan of Utah, United States to identify the best change detection method among image differencing, image regression, TCT, and CHI-square Transformation concluded that none of the above mention algorithms has defined change (Deng et al., 2008). presented PCA and hybrid classification results revealed that PCA based change detection yielded better accuracy rather than a post-classification based approach in an urban environment (Varshney et al., 2012). has proposed a new algorithm MCVA detect LULC changes in comparison with ICVA and post-classification resulting overall accuracy of MCVA was 64% while ICVA was 60% and post-classification was 56% (Sharma et al., 2011). assessed LULC changes using post-classification change detection by comparing three different classification approaches (iso-data, MLC, and fuzzy rule base) resulted in fuzzy rule-based classification achieve overall high kappa values than other classification techniques (Kamh et al., 2011). compared five different change detection methods to evaluate urban land cover changes among which the post-classification change detection technique was found to be much appropriate (Vorovencii, 2014). compared change detection techniques to detect LULC changes over time by proposing image differencing, NDVI differencing, PCA, and post-classification change detection techniques resulted in NDVI differencing achieved high overall accuracy and kappa value (Du et al., 2014). assessed the comparison of sub-pixel change detection methods with traditional CVA and PCA to analyze urban areas which revealed that sub-pixel change detection methods are much appropriate to detect changes in urban areas (Minu and Shetty, 2015). compared image differencing, image ratioing, CVA, PCA and TCT change detection methods to detect changes in agricultural land area and the results were compared with supervised classification MLC by post-classification change detection technique to assess the effectiveness and accuracies which revealed that CVA was the most appropriate technique to detect changes in agricultural land (Hossen et al., 2018). assessed and predicted future LULC changes in Manzala lake using different classification techniques by proposing unsupervised iso-data clustering, MD, MLD, MLC, and NDWI which resulted in MLC as the most effective technique and overall high accuracy (Table 2).

Remotely sensed data always vary in spatial, radiometric, spectral, temporal resolutions and different types of sensors which may result errors in image classification, so the selection of appropriate change detection methods is very much necessary, as concluded in this literature that for a classified remotely sensed data whether supervised or unsupervised post-classification comparison technique is the best for change detection of a landscape with multiple LULC classes while a landscape with complex LULC features which cannot be easily evaluated using traditional pixel by pixel classification techniques require some advance classification techniques such as sub-pixel classification, decision rule-based classification and fuzzy classification for precise evaluation of LULC features. The extraction of single land feature to assess change and no change or rate of change using remotely sensed data depends upon the landscape features such as humidity, soil moisture, sun angle and spatial resolution which justify the selection of appropriate change detection method.

4. Selection of appropriate change detection method

In the field of remote sensing, analysis of the raster image for the selection of appropriate change detection method is important to extract useful LULC change information. The satellite image raw data may vary due to geometric and radiometric flaws because of the curved shape of

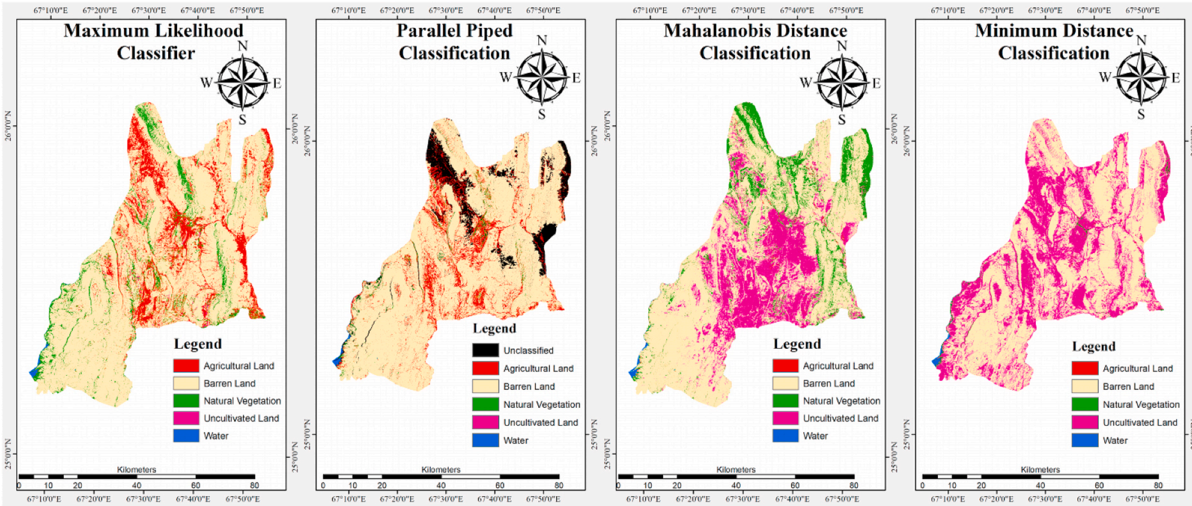

Fig. 1. Classified map of Khirthar national park.

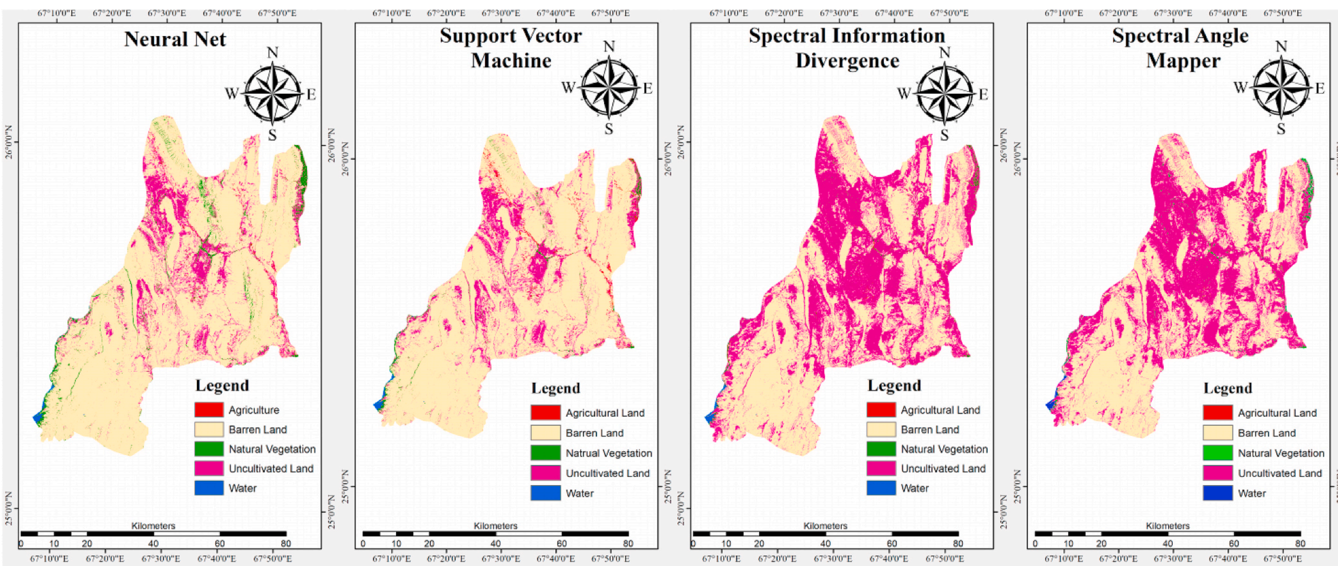

Fig. 2. Classified map of Khirthar national park.

the earth, which may yield errors in image classification. So before the selection of the change detection method, it is important to remove these distortions. Generally, visual interpretation is the initial step in remote sensing to follow for the selection of appropriate change detection methods based on research needs. It acknowledges a researcher about the on-ground objects and structures of the particular area of interest. Through visual observation of satellite images, it can be experienced that the particular area has a single land feature or multiple land features (e.g. forest, urban, waterbody, agriculture, etc.). On behalf of that, change detection techniques are further divided into pre and post-classification approaches. The pre-classification approaches are mostly used for change and no-change, rate of change, and image enhancement. And the post-classification approaches are widely used for "from-to" change analysis and comparison of individually classified images (quantitatively and qualitatively). Therefore a study area having a single land feature to evaluate change than it would be better to choose pre-classification change detection techniques. And if a study area having multiple lands features it would be better to choose a post-classification change detection technique to evaluate quantitative and qualitative results.

The post-classification change detection approach is based on the results of image classification. Usually, these classification techniques are difficult and time-consuming task but produce good quantitative and qualitative results along with a matrix of change. The major advantage of these techniques is the neglect of atmospheric and environmental distortions. Based on the training sample data, sometimes classification yields unsatisfactory results of historical data but using the spectral information of land features in support with high-resolution satellite imagery (e.g. Google earth) results better in accuracy assessment.

Most of the studies have implemented post-classification comparison as change detection using different classification techniques. Similarly, this review has also applied a comparative analysis of different classification techniques on **Khirthar national park (case study)** to justify the best among them. Landsat 8 (OLI & TIRS) satellite data of 2019 was used to analyze the hierarchy of classes and found 5 different LULC classes named as agricultural land, natural vegetation, barren land, uncultivated land, and water. The analysis of classification techniques such as MLC, parallel piped, MLD, MD, spectral information divergence, spectral angle mapper, neural net, and SVM was used to understand the effectiveness and efficiency by comparing their overall accuracy and kappa statistics. The quantitative and qualitative evaluation of these classifications are monitored in the same environment that helps in

Table 3
Accuracy assessment of different classification.

Classification Technique	Classified Pixels/ Total Pixels	Overall Accuracy	Kappa Statistics
Support vector machine	2376/2433	97.6572%	0.9640
Maximum likelihood classifier	2371/2433	97.4517%	0.9610
Neural network	2359/2433	96.9585%	0.9532
Mahalanobis distance	2228/2433	91.5742%	0.8735
Minimum distance	2033/2433	83.5594%	0.7635
Spectral angle mapper	1934/2433	79.4903%	0.7047
Spectral information divergence	1928/2433	79.2437%	0.7006
Parallel piped classification	1676/2433	68.8861%	0.5294

getting the best results (Figs. 1 and 2).

From the classification results, it is seen in Table 3 that the support vector machine, maximum likelihood, neural network, and mahalanobis distance excelled in high accuracy. Minimum distance, spectral angle mapper, and spectral information divergence achieve moderate accuracy while parallel piped achieves low accuracy. The results of different classification showed that the Support vector machine is best suited however during assessment it revealed the actual on-ground situation was in favor of MLC. The support vector machine classified every pixel according to the dominant value of the pixel which results in the low agriculture crop and natural vegetation area classified into uncultivated or barren land. Likewise, all other classifications were less effective in comparison to maximum likelihood. Thus the selection of the change detection techniques concludes that the post-classification approach using MLC is an appropriate change detection method.

5. Thematic accuracy assessment

Accuracy assessment methods are used to validate the LULC map classification processes which decide the quality of gathered information justifying that the image pixels are well classified or misclassified from remotely sensed data. These accuracy assessments can result qualitatively which is usually a comparison between classified LULC map and on ground situation or quantitatively to identify and quantify by comparing classified map data with reference data, which is very much important for developing results assessment and decision-making. A variety of accuracy assessment methods has been discussed in the previous remote sensing literature (Aronoff, 1982; Kalkhan et al., 1996; Koukoulas and Blackburn, 2001; Piper, 1983; Rosenfield and Fitzpatrick-Lins, 1986) to verify image classification and were difficult to implement because of problems in field data sets therefore most of the researches in the past didn't provide quantitative results due to that some new accuracy assessment methods were developed for change detection (Lowell, 2001; Morisette and Khorram, 2000) among which currently confusion matrix or error matrix is the most common technique for accuracy assessment based on some factors such as collection of ground control points (GCPs), classification scheme, sampling type, spatial auto correlation and size and unit of sample (Congalton and Plourde, 2002). The commission errors, omission errors, overall accuracy and khat or kappa coefficient are the important elements in accuracy assessment which can be developed using error matrix. Error matrix define errors in LULC map classification which could occurs due to presence of an image pixels in a class are basically assigned to another class resulted as commission error and omission error. Commission errors occur when a presence of image pixels is incorrectly classified and does not belong to that class and are measured as false positives while omission errors occur when evaluated image pixels are found in a different class and are measure of false negatives. Omission errors in one class could result as commission error in other class. Commission errors are the example of user's accuracy which is the probability of correctly classified values in a given class and omission errors are the example of producer's accuracy which is the probability of predicted values actually belongs to that particular class described as an example in (Table 1), while the ratio between the sum of all correctly classified values which are located diagonally in the error matrix from upper left to lower right and the reference values describes the overall accuracy (Table 4) which is very much essential to know that how much portion of LULC map has been correctly classified.

Error matrix not only calculates the user, producer and overall accuracy but also allows calculating the kappa statistics which is generated to evaluate the percentage of well classification has been performed. Kappa coefficient of agreement justifies the classification performed perfect agreement or just equal to random or no agreement. User, producer and overall accuracy assessment is basically a chance result in certain accuracy and to get rid of the influence of chance; kappa estimation can be done by calculating coefficient of agreement and mathematically represented as

$$K = \frac{N\sum_{i=1}^{r}(x_{ii}) - \sum_{i=1}^{r}(x_{i+} \; x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \; x_{+i})}$$

According to above example of error matrix.

r = number of rows in the classification table
N = total number of points = 100
x_{ii} = sum of correctly classified points along the diagonal = 28 + 20+16 + 9 = 73
x_{i+} = total number of points in row i
x_{+i} = total number of points in column i

$$\sum_{i=1}^{r}(x_{i+} \; x_{+i}) = (38*35) + (23*25) + (24*21) + (15*19)$$

$$= (1330) + (575) + (504) + (285) = 2649$$

$$K = \frac{(100*73) - 2649}{(100)^2 - 2649} = \frac{4651}{7351} = 0.6327$$

Table 4
Assessment of overall accuracy.

	Class types determine from reference source						
Class types determined from classified map	# Classes	Urban area	Water	Forest	Agriculture	Totals	User's accuracy
	Urban area	28	1	4	5	38	73.68%
	Water	2	20	0	1	23	86.95%
	Forest	3	1	16	4	24	66.66%
	Agriculture	2	3	1	9	15	60%
	Totals	35	25	21	19	100	
	Producer's accuracy	80%	80%	76.19%	47.36%		
Overall accuracy	(Sum of correctly classified pixels/total reference pixels) * 100					(73/100) * 100 = 73%	

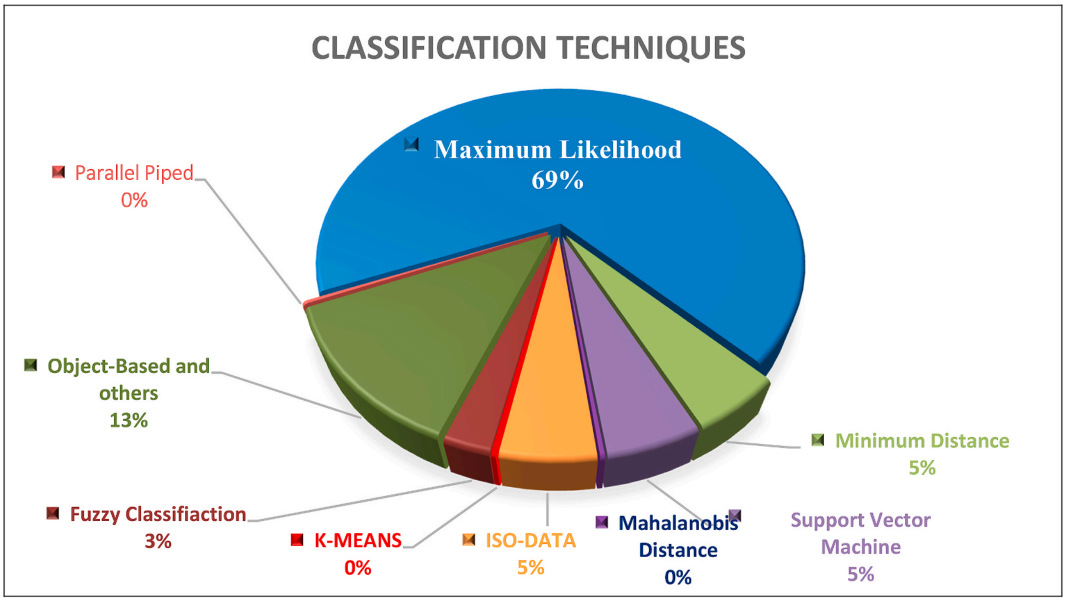

Fig. 3. Pie Diagram of classification techniques mostly used.

K% = 63%

Accuracy assessment of LULC change detection of remotely sensed data plays an important role in remote sensing and for the further information interested candidate should look at these two books (Biging et al., 1999), and (Congalton and Green, 2008).

6. Conclusion & recommendation

The multi-temporal satellite images of the same sensor are prerequisites for determining the change and selection of appropriate change detection algorithms to achieve good change results. The analysis for the selection of appropriate change detection is a dynamic research topic and newer techniques are still being developed. This paper has a detailed review of change detection methods applied on different study areas but none of the single change detection methods is applicable at all cases (A. Ayanlade, 2017; He et al., 2013; Hussain et al., 2013; Lu et al., 2004; Macleod and Congalton, 1998; Thyagharajan and Vignesh, 2019) except the post-classification approach. The post-classification techniques are widely used in most of the research studies and achieve high overall accuracy. As far as this review paper is concerned, many change detection methods have been implemented to assess, monitor, and classify LULC changes. Despite some important factors in consideration that are necessary to observe the desired study area to achieve acceptable or high accuracy. During the review research, the comparative analysis was also performed between classification techniques, which results in the MLC as the best classification technique for the post-classification change detection method. It was also observed during the literature review that most of the studies used a post-classification approach for change. So that's why a diagram was designed for the classification techniques used from 1998 up to the present in Fig. 3.

Above all, it is very clear from the above pie diagram that there were numerous change detection methods used in the past two decades among those post-classification using MLC is widely used. In practice, several change detection techniques are often used to implement change detection, whose results are then compared to identify the best product through visual assessment or quantitative accurate assessment. The selection of a suitable change detection method requires careful consideration which has been discussed in section 4. The major finding of the present study is that all methods are not hundred percent accurate, but post-classification yields useful information and should be viewed as complementary in comparison to the others. Therefore it is suggested to research scholars, the scientific community, and resource managers to apply the mentioned approach for change method to get the remarkable results that will be helpful in high thematic accuracy and acceptable outcomes to prevent further losses.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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