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ABSTRACT

Background/Purpose: *The objective of this literature review is to explore different land use and land cover methods using machine learning techniques and also their applications in change detection. Reviewing various methods adopted in this domain opens up a new path for taking up further research by extending the current approaches.*

Design/Methodology/Approach: *The research findings presented in various scholarly articles are collected from secondary resources including scholarly journal publications. These articles are analyzed, and the interpretations are highlighted in this review paper.*

Findings/Result: *This research provides insight into various techniques used to classify remote sensing imagery. The gaps identified during the analysis with different approaches have helped to get a clear picture when formulating research questions in the remote sensing geographic information systems domain.*

Research limitations/implications: *This study has surveyed various applications of remote sensing in GIS. This study is limited to a review of the various machine-learning approaches used for implementing change detection. The various deep learning architectures for image classification could be further explored.*

Originality/Value: *The articles selected for review in this study are from scholarly research journals and are cited by other authors in their publications. The papers selected for review are relevant to the research work and research proposal presented in this paper.*

Paper Type: *Literature review paper.*

Keywords: Land use land cover (LULC), Machine learning, Remote sensing, Change detection

1. INTRODUCTION :

The classification of human activity and natural components in landscapes over time is called land use/land cover (LULC) and is based on established scientific and statistical methods for examining relevant source data. Earth observation is concerned with the gathering of information about the biophysical systems on the earth’s surface, observing and modeling the interactions of the earth’s surface processes with the atmosphere. The location and attributes of spatial features are considered geospatial data. Such data can be collected, stored, analyzed, and displayed using a computer system comprising data and databases, hardware, software, people, and organization which is called a Geographic Information System(GIS). Map creation, spatial dataset management, advanced spatial analysis, concurrent visualization of various spatial datasets, and location-based query resolution are all capabilities of geographic information systems. GIS maps are visual representations of quantitative data [1-2]. By detecting the electromagnetic radiation reflected and transmitted from the earth's surface, remote sensors can gather data about a region or specific items there. Information from such remotely sensed images can be extracted and analyzed for making interpretations in GIS. Such Remote sensing geospatial technologies have advanced from the analysis of aerial images to the interpretation of satellite images. Remote sensing images are used in various applications such as mapping land use land cover, forestry, agriculture, urban planning, geomorphological surveying, etc [3]. The advent of new aerial and satellite sensors and platforms, as well as state-of-the-art statistical techniques, GIS, and anticipating models, have given researchers a variety of techniques for mapping vegetation [4][5]. Using satellite data, researchers are investigating different strategies for data storage and processing, including machine learning, deep learning, and cloud computing. Precision agriculture involves the application of such advanced techniques and attempts to improve agriculture production by optimizing agricultural inputs [6].

A GIS incorporates imagery obtained through remote sensing. Remote sensing is the study of the earth using sensors aboard aircraft and satellites. These sensors capture data as images and provide particular capabilities for changing, interpreting, and displaying those images. Remote sensing indices are derived for various combinations of satellite spectral bands. A spectral index, which represents the relative abundance of an interesting feature, is a composite of spectral reflectances at two or more wavelengths. These are calculated from multi-band images by band addition and band subtraction, resulting in a range of band ratios. There are various applications of satellite indicators studied in previous studies, including applications in agriculture, water resources, urban development, forest ecology, geology, soil science, vegetation, and others. The vegetation index which is the subset of spectral indices makes green vegetation more prominent so that plants stand out from other visual elements. The reflectance of light spectra from plants vary depending on the type of plant, the amount of water in the tissues, and other internal variables. The chemical and structural properties of an organ's or leaf's surface, such as the leaf's structure and pigments, etc., determine the vegetation's reflectance. Initially, intrinsic indices were created using straightforward band ratios, highlighting the spectral characteristics of plants at various growth and senescence stages. Applications for vegetation indices include crop condition monitoring and crop yield prediction, biodiversity assessment, estimation of biophysical parameters, phenological assessment, vegetation health/stress, forest degradation, biomass mapping and modeling, productivity and carbon assessment, and vegetation health/stress. There is a need to design optimal indexes for specific remote sensing applications and particular instruments as the instruments do not provide data for all spectral bands. Various application-specific approaches are available in the literature for designing optimal vegetation indices [7-9].

This paper attempts to review the research progress in LULC mapping and change detection. The study reviews the use of LULC classification systems on a regional and global scale and an attempt is made to identify the associated challenges and research gaps concerning LULC change. This paper consists of various sections that meet all the objectives outlined in Section II.

2. OBJECTIVES :

The primary aim of this review is to collect the results of different studies in the area of land-use analysis and to analyze the approaches used to develop interpretations that provide ideas for filling gaps in this field and take up further research in this domain

(1) To study the methods used for land use land cover analysis with the use of remote sensing data
(2) To study land use land cover mapping and change detection.
(3) To study the use of remote sensing and GIS in the agriculture domain
(4) To study image classification methods used in remote sensing
(5) To study the current status and analyze the existing approaches
(6) To arrive at an ideal solution based on the current status
(7) To identify the research gaps
(8) To frame the research agenda and put forth the research questions
(9) To analyze the research agenda
(10) To arrive at a research proposal
(11) ABCD Analysis of the research proposal

3. METHODOLOGY :

Remote sensing images will be collected using Earth Explorer which is a free open browser platform for downloading aerial or Lansat satellite imagery. Google earth engine provides satellite images and geospatial data sets. The images have to undergo preprocessing and are later used for classification using the machine learning method. Spectral bands and indices derived between a certain period from the multi-temporal imagery will be used for change detection.

4. REVIEW OF LITERATURE/ RELATED WORKS :

Various models and comparative studies of the approaches are available in the literature. The related research articles are collected and used for presenting the research findings. Various articles are collected from Google Scholar using the Advanced Search option by specifying the keyword 'Land use land cover analysis' and dated between 2017 to 2022. Table 1 summarizes the results of this search.

Table 1: Scholarly literature on Land use land cover (LULC) analysis.

S. No.	Area of Study	Focus	Outcome	References
1	Data analysis for remote sensing.	The current state of research and applications is presented with a case study based on the LULC meta-analysis.	The authors present a systematic study covering the landscape change process, the main features of study sites, and also landscape pattern analysis. The rapid development of techniques for analyzing remotely sensed data and its relevance to agroecosystem and forest research is an important conclusion.	F. Malandra, et al. (2018). [10]
2	Analyze multispectral satellite imagery using machine learning techniques.	Detecting Land Use Change from Landsat Time Series Imagery of the Pao River Basin in Venezuela.	A comparison of the pixel-based direct comparison approaches with the object-based method and classification-based change detection. Artificial neural networks when employed in classified object-based change detection approaches produced reliable findings. While urban, agricultural, and vegetation classes were linked to negative indices, the study found favorable area differences for classes including rangeland and water.	Márquez-Romance, et al, (2022). [11]
3	LULC mapping using machine learning algorithms on satellite images.	Identifying the best classifier for further earth observation applications among the various machine learning algorithms.	The study shows that among the six Machine Learning techniques investigated, including RF, Support Vector Machine, spectral angle mapper, ANN, Fuzzy ARTMAP, and Mahalanobis distance. RF and ANN approaches may be employed efficiently for LULC classification. The assessment of accuracy was performed by applying index-based validation techniques, receiver operational curve, root mean square error, and kappa coefficient methods.	Talukdar, et al. (2020). [12]

4	Deep learning approaches for LULC classification.	Using pre-trained deep learning models using remote sensing images and improving the performance of LULC classification.	Deep Transfer Learning Models namely Resnet50V2, Inception-V3, and VGG-19 are used for classification. The selected hyperparameters were adjusted for improving the classification accuracy. The early stopping technique is used to improve model performance by reducing overfitting. The generated models can be used to manage natural resources and promote sustainable growth in urban and agricultural planning.	A. Alem and S. Kumar, (2022). [13]
5	Examination of alterations in land use and cover.	Calculation of the Normalized Ratio Urban Index (NRUIms) which is a new spectral index for analysis.	The study demonstrates that the suggested NRUIms boost separability between various LULC class pairings when combined with other current spectral indices as an extra feature. Time series analysis for the years 1991 to 2019 reveals that the studied area has experienced extraordinary urban growth.	Piyoosh, A. K., & Ghosh, S. K. (2022). [14]
6	LULC change analysis in the Kashmir valley.	Time series analysis between the period from 1992–2001–2015.	LULC maps are generated using a maximum likelihood classifier for the study area for the identified period. For analysis, a collection of Landsat satellite images are employed. Three patterns indicating changes in land use and land cover have been spotted, and significant differences are seen in the study area.	Alam, A., Bhat, et al. (2020). [15]
7	Urban surface heat island (SUHI) analysis.	Using satellite information to find out how land use and cover have changed.	Vegetation cover is calculated with the use of the Normalized Difference Vegetation Index (NDVI) and land use has been assessed through the use of a selection tree primarily based totally on the CRUISE algorithm. Farmland is showing signs of impervious surface expansion, which is causing a decrease in vegetation cover, progressively raising the temperature of the land, and causing the SUHI effect.	Wang, H, et al. (2017). [16]
8	Forecasting principal	Building a hybrid model which is	In this study, a hybrid model for LULC change prediction is	Márquez, A. M, et al. (2019). [17]

	component 1 in the future time.	identified as a kriging ordinary-forecasting model.	presented utilizing the surface reflectance of a satellite image as a predictor variable that has transformed the principal component 1. The proposed approach can be used to create LULC change prediction maps over time series, assess spatiotemporal trends of predictor variables, and predict changes in LULC.	
9	Analysis of various change detection methods	Examining the basic procedures needed for detecting changes and emphasizing the difficulties and problems encountered in this area.	The essential framework for the change detection technique is presented. This article provides an analysis of remote sensing data preprocessing, different image segmentation methods, and key change detection methods such as fuzzy, neural networks, transforms, and algebra-based approaches. Classification, transformation, and transformation-based approaches, as well as transformation-based change detection, are discussed. It also discusses how the change detection techniques' performance and accuracy are evaluated.	A. Asokan, et al. (2019). [18]
10	Image classification.	Analysis of remote sensing image classification using spectral statistics.	This document provides a summary of the research activities and lists the phases of image processing used in remote sensing applications, change detection techniques, and performance evaluation techniques. The techniques suitable for specific applications are also discussed.	A. Asokan, et al. (2020). [19]

One of the often employed techniques is remote sensing for collecting physical data and integrating it with GIS. Remote sensing image processing techniques are widely used in tackling various real-life applications and have a significant impact on issues related to the economy and environment. Table 2 presents the summary of the literature survey done using Google Scholar with the keyword ‘Remote sensing GIS’ for the articles published between 2020 to 2022.

Table 2: Literature study on Remote sensing GIS

S. No.	**Area of Study**	**Focus**	**Outcome**	**References**
1	Remote sensing data	Study of the impact of using data capturing	This research provides information on the effects of various remote sensors,	A. Goswami, *et al.*, (2022). [20]

	acquisition methods	methods on automatic change detection.	image-capturing, and image-processing methods. The ability to detect changes in remote sensing photos using algebraic and machine learning techniques is examined. This study relies on pixel-by-pixel classification and does not consider spatial information while classifying the image.	
2	Removing haze from remote sensing images with high-resolution.	Providing a GAN-based optimization framework.	Generative Adversarial Network (GAN), a single picture Dehaze technique developed using a cellular neural network, is used to solve texture information loss. The distortion of the picture details is reduced by utilizing both global and local discriminators and this texture attention map guarantees to keep the details of ground features.	Zhang, X, (2022). [21]
3	Convolutional Neural Network (CNN) model with image time series as input.	Crop distribution map generation method from remote sensing imagery.	The authors suggested a convolutional neural network (TS-OCNN) for time series which is object-based. This method for classifying agricultural crop kinds makes use of multi-temporal remotely sensed imaging with a fine spatial resolution (FSR). For field management and agricultural yield forecasting, precise crop distribution mapping is offered. This method's key benefit is that it may be simply applied to other landscapes.	H. Li, et al. (2022). [22]
4	Study of image analysis techniques using deep learning.	Techniques for image registration in remote sensing applications are reviewed, and the challenges and future scope of research are presented.	This article provides a comprehensive analysis of image registration methods used on remote sensing images. An examination of deep learning and image-based approaches is included in the main discussion. A comparison-based study of newly proposed approaches is provided.	Paul, S., & Pati, U. C, (2021). [23]
5	Feature reduction	Classification of Hyperspectral remote sensing	Several feature reduction algorithms based on PCA, including FPCA, SPCA,	Uddin, M. P., et al. (2021). [24]

	technique based on PCA.	image and dimensionality detection.	SSPCA, KPCA, KECA, and MNF have been investigated to bring out unique features from hyperspectral image data. The study examines Indian Pine and Washington, DC Mall HSI rankings against several key performance indicator indices.	
6	Study of various manual and digital classification methods.	Review of land classification processes.	Different classifiers for land use and cover are highlighted. Consequently, the analysis and object-based categorization techniques are superior to pixel-based techniques. Better outcomes in terms of computation accuracy are obtained when spatial information is combined with spectral information. Additionally, the study shows that Light Gradient Boosted Machine models that use hyperparameters for classification outperform those that use limited parameters.	Alshari, E. A., & Gawali, B. W. (2021). [25]
7	Use of NDVI spectral index for assessment of forest and grassland health.	Review of applications for assessing the health of forests and grasslands based on GIS and remote sensing.	The study investigates the numerous ecological characteristics, markers, and measurements related to assessing the health of forests and grasslands. This indicates that most studies use NDVI as the vegetation index. The study also highlights the fact that not all remote sensing data can be used to accurately extract perceived indicators due to resolution limitations.	Soubry, I., et al. (2021). [26]
8	Analysis of a West Bengali city's urban growth.	Defining the various forms of urban growth and evaluating accuracy.	The study uses the hard classification technique called Maximum Likelihood Classification. The survey targets are classified into 5 categories and their accuracies are evaluated. Pearson's chi-square statistic is used to determine the degrees of freedom for city growth. The study identifies unique features of urban	Roy, B., et al. (2021). [27]

			growth that can be further investigated in small towns. The study can be used by local planning authorities for planning and managing urban growth.	
9	Time series analysis.	Quantification of urban growth over 20 years that is analyzed in the time interval of 5 years using supervised spectral classification.	The study follows a systematic sequence of steps involving preprocessing of images from Sentinel and Landsat, supervised spectral classification to identify LULC types, analysis of temporal and spatial changes in the selected area, and finally the analysis of land consumption by relating to population. The study also includes the urbanization growth analysis using Land Use Efficiency.	Wiatkowska, B., et al., (2021). [28]
10	Deep neural network.	Development of a model for pixel-wise image labeling was developed for building extraction from satellite imagery.	In this research, a paradigm for noise-adaptive deep neural networks is provided, where a base network is followed by an extra probability transition module. It captures the relationship between true and noisy labels. For creating the model, backpropagation is employed. The study's findings demonstrate how much less manual annotation work is required to extract objects from remotely sensed aerial photography.	Zhang, Z., et al. (2020). [29]
11	Classification of remote sensing scene images.	Building Self-compensation convolution neural network (SCCNN) for better performance.	By using fewer filters, this method lowers the temporal complexity of the convolutional neural network, and the convolutional channels are compensated by the input features. Feature extraction is improved by using self-compensating convolution with a wider channel shortcut. The bottleneck modules are reused with the same structure in the proposed model.	X. Cheng and H. Lei, (2022). [30]

5. DETECTION OF CHANGE IN REMOTE SENSING IMAGES AND LULC MAPPING :

Techniques for detecting change using remote sensing GIS are depending on detecting discrepancies in two satellite images before and after a particular event. GIS change detection algorithms compare spatial representations from two-time points to measure differences in variables of interest.

By extracting super pixel-based change characteristics, the authors of the paper [31] have provided a framework for detecting the change in multispectral remote sensing imagery. This work uses a neural network for learning hierarchical difference representation. Deep neural networks are used for change detection where the neural networks are capable of transforming the original image to high-level features and extracting the key information from these features by eliminating irrelevant noise information. Temporal characteristics are extracted from superpixels and an object-based deep learning model is introduced in [32]. By developing a change detection method for multi-temporal hyperspectral pictures, the authors of [33] have demonstrated the usefulness of deep neural networks. An end-to-end network using a convolutional neural network and a recurrent neural network for multitemporal remote sensing image analysis shows good performance in comparison with other previous techniques for detecting change [34]. The post-processing approach is introduced in [35] for enhancing the results of the detection of land cover change. The raw change detection accuracy is refined in this approach by using multi-scale segmentation and expectation maximization algorithms. The Normalized Difference Vegetation Index (NDVI) and the Normalized Burn Ratio (NBR) are employed in [36] as forest greenness indicators for the proposed algorithms of basic z-score, harmonic z-score, and linear trend, which are utilized to detect changes in the condition of the forest. The mean and standard deviation of the baseline period and analysis years are used in the basic z-score method and BFAST and EWMACD methods are used in e harmonic z-score method. By thresholding the summarized z-score value, change is identified. Performance analysis of different change detection algorithms on heterogeneous image pairs based on Receiver operating characteristics (ROC) curves, processing time, and visual observations of the change detection score images is presented in [37]. The approach proposed in [38] models repeated changes in the source domain by defining decision rules for the target domain image pair, supported by reference data available only in the source domain image pair. increase. [39] presents a change detection method that is unsupervised and cross-sharpening of multitemporal images integrating the intercept, slope, and correlation indexes, and image segmentation concepts are implemented to reduce detection errors due to spatial displacement with images having different acquisition angles. In [40] the spectral channels are transformed into suitable feature space for reducing redundancy and avoiding noise. Deep Belief Networks in combination with feature change analysis are used in this unsupervised change detection approach. The correctness of geometric registration is important as the change detection techniques are dependent on them. Quantitative evaluation of the performance of various techniques in different environments plays an important role to achieve optimal results [41].

The three main techniques for change detection after categorization are picture subtraction, image ratio, and change detection [42]. The article [43] compares the effectiveness of the multiresolution analytical wavelet transform method with additive seasons and trends (BFAST) and seasonal trendless breaks for the BFAST method in terms of how the monitor is modeled and Identifies changes in land cover. seasonal variation. LULC mapping problems are handled with temporal change detection techniques. Supervised and unsupervised techniques are used for classifying remotely sensed images. Urban growth analysis uses temporal variations using the image attributes such as built-up, water, vegetation, and barren land. Landsat images are successfully used for the study. Different thematic LULC maps highlighting the relation between the forest cover and the associated LULC classes are created to study the changes in vegetation. PCA is used for identifying the set of metrics of Landscape Analysis and to study spatiotemporal urban dynamics [44-46]. LULC classification models using a Random Forest classifier are generated by integrating Sentinel 1 and Sentinel 2 images. Textural image analysis and vegetation indices are used in the study. Another approach has used a regression model to study the negative effects of urban expansion [47][48]. Recent applications have acquired data from Landsat 8 and Sentinel 2 for analyzing remotely sensed data. Potential use of Landsat 8/ OLI and Sentinel 2/ MSI are analyzed and also a time series study on using medium-resolution multispectral optical data [49][50]. High spatial resolution aerial images of Earth are used in the framework proposed in [51] where the landslide spatial information is considered by multi-segmentation of the post-event image and object-based majority voting. Multi sensor multi temporal satellite imagery is

used for change detection using Principal Conmponent Analysis(PCA) in [52] showing accurate results.
The flowchart in Figure 1 below shows the overall procedure for LULC classification using satellite imagery.

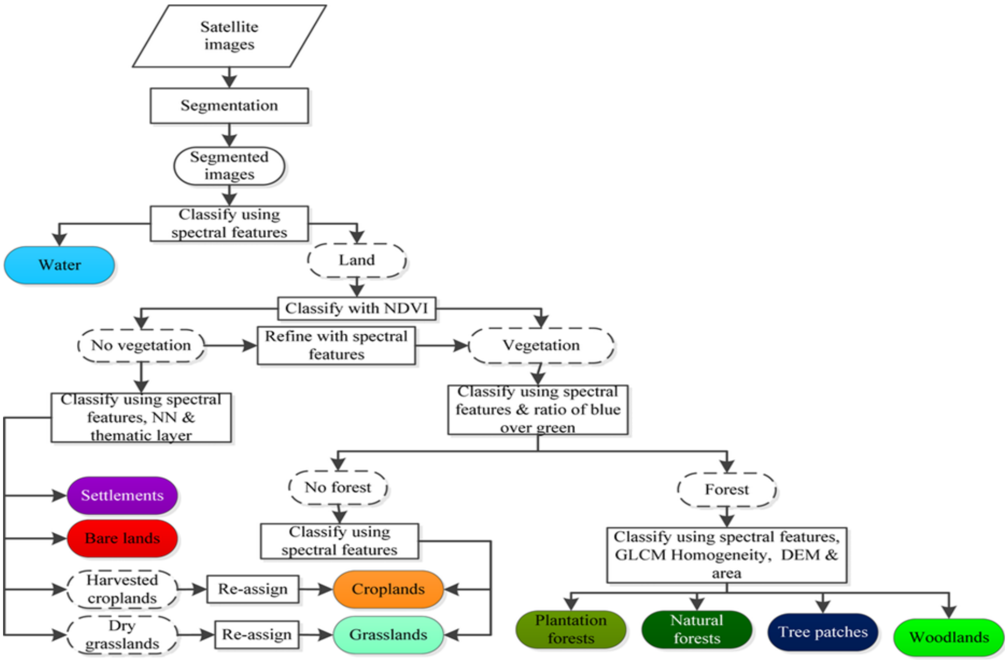

Fig. 1: Land use land cover classification[53].

6. REMOTE SENSING AND GIS APPLICATIONS IN AGRICULTURE :

Earth remote sensing is essential in agricultural research because crops are so sensitive to soil changes, climate, and other biophysical factors. Crop biological life cycles are closely associated with strong seasonal patterns when monitoring agricultural production systems. These characteristics are all incredibly spatially and temporally varied. In agriculture, timely crop monitoring is crucial, and remote sensing techniques can aid with this. There are numerous uses for remote sensing in agriculture, including weed control, crop condition assessment, insect and disease monitoring, and water and nutrient status monitoring. Precision agriculture, crop yield, and production forecasting are discussed in [54]. Water resource management plays an important role in agriculture and also in all ecological processes. The Spatio-temporal changes in the surface water area are analyzed using environmental variables which are specified using spectral indices such as EVI, NDVI, and NDWI[55]. This study is applicable for monitoring changes in surface water due to changes in atmospheric conditions. The analytical model framework and the sensitivity analysis presented in [56] are suitable for water management in large-scale water resource systems. Hierarchical analysis in combination with the fuzzy Technique for Order of Preference is used in this decision-making model. Another water resource management model is presented in the paper [57] using the GIS database and graph theory by modifying the GIS graph data and equipment management system. Seasonal variations of land use land cover and land surface temperature(LST) and the association of LULC with LST are explored and presented in [58]. The major LULC indices used for analysis include NDVI, NDBI, NDBAI, and MNDWI.
We can use time-series analysis to track land use/cover changes within a given agricultural area to update water management strategies[59]. An evaluation of three Land Surface Temperature algorithms including RTE, SCA, and MWA for sensitivity analysis by considering daytime and nighttime LST values is presented in [60]. Using LST and NDVI the effect of global climate change is studied in [61]. Time series analysis of water quality and land use is presented in [62] proving the importance of geospatial analysis using satellite images. Estimation of flooded crop acreage using satellite images can be effectively done by creating time series of crop condition profiles [63]. A GIS map of crop disease and crop disease risk can be created in various ways. Many examples available in the literature demonstrate some of the ways in how GIS and geostatistics can be applied to the agricultural

environment. Despite this, there is no single solution found in the literature proposing a solution to the management of all crop diseases. GIS is of little use if the spatial pattern is uniform. However, perhaps in contrast to the uneven pattern. On the other hand, geospatial data can be distorted and misleading if patterns change faster than the data is collected. The application of geostatistics is theoretically constrained. This is because the geostatistical model that the surface of the earth is mapped by spatial analysis is not always applied. All the spatial analyses do not require the use of Geostatistical analysis [64]. A cropland classification map is presented in [65] using Random Forest and Support Vector Machine algorithms using Sentinel 2 MSI data. VV and VH backscatter and their ratio from Sentinel 1 are used with Sentinel 2A NDVI data for crop classification using major algorithms such as Cubic support vector machine, Random Forest, Decision Tree, Ensemble classifier, and Nearest Neighbor are implemented in [66]. cubic SVM is found to be more efficient with the use of NDVI. [67] shows that multi-spectral and multi-temporal information compared with other bands, red-edge band 1 (RE-1) and shortwave-infrared band 1 (SWIR-1) of Sentinel-2 are giving better results in crop classification. Neural networks are efficiently used for crop classification. Pixel-based and object-based approaches are used in deep learning with Recurrent Neural networks and Convolutional Neural Networks [68]. The papers [69] and [70] give a comprehensive review of using machine learning methods in the agriculture domain and the major finding is that Artificial Neural Networks are more efficient. An assessment of Deep Learning techniques used for LULC classification is presented in the article [71] highlighting the complexity of standard machine learning approaches and the flexibility of deep learning architectures proving the best performances.

A study on the spatial spread of rice disease called rice blast and potential risk areas for this disease is being conducted in the rice ecosystem of Karnataka[72]. Crop suitability and crop pattern mapping using remote sensing GIS techniques are implemented using Landsat 8 data with NDVI and supervised classification methods. The potential application of GIS in various farm operations is discussed in [73]. Various studies using pixel-based and object-based analysis on the mono-temporal remote sensing imagery for crop type classification have proven the use of earth observation technology in this area [74][75]. Multi-temporal remote sensing images were also used efficiently for crop type classification [76-80]. It is found that multi-temporal image analysis has outperformed in terms of giving accurate results. One such comparison proving the effectiveness of multi-temporal image analysis with single-date image analysis is given in the article [81]. The article [82] provides a literature review of how digital technologies are applied in the agriculture domain for predicting crop type and crop phenology.

7. IMAGE CLASSIFICATION TECHNIQUES IN REMOTE SENSING :

Processing of remotely sensed images requires to undergo several stages including preprocessing, image enhancement, and image classification. The different steps in the processing of remotely sensed imagery are described in this section. Stationary cameras, hyperspectral cameras, or radar antennas attached to satellite sensors are all used to capture remote sensing images. Sensors, detectors, and devices such as cameras and scanners are used to detect electromagnetic radiation. There are mainly two types of instruments that are used for image acquisition based on energy sources. While energy emitted by an antenna toward the surface of the earth is employed in active remote sensing, solar radiation is used as the illumination source in passive remote sensing. It is measured how much electromagnetic radiation makes up the energy that is dispersed back [83][84]. The fusion of various types of remote sensing data with supplementary data from various sources is the driving force behind several new scientific research [85].

The resolution of a digital image refers to the quantity of visible detail described in terms of pixel dimensions indicating how many pixels are displayed per inch of an image. More detailed information is observed with smaller pixel sizes indicating higher resolution. Variations in satellite picture resolution would be influenced by the orbit of the satellite and the sensor's construction. There are four different forms of resolution for remote sensing systems, including spectral resolution and radiometric resolution. both temporal and spatial resolution. The width and number of spectral bands are referred to as spectral resolution, which refers to a sensor's capacity to distinguish between smaller wavelengths. Spatial resolution represents the number of pixels in the image which means an image having a higher spatial resolution is made up of more pixels than that of a lower spatial resolution. The amount of information kept in each pixel is the number of bits utilized to represent the energy that was recorded in each pixel or the radiometric resolution. Temporal resolution is the time it takes the satellite to complete one revolution and return to the same observation area. A three-dimensional array with the two-dimensional spatial correlation of accurate spectral information combination is used to represent a spectral image. Hyperspectral imaging and multispectral imaging are the two types of spectral imaging techniques. Hyperspectral imaging takes many images for the same spatial area at different wavelengths and multispectral imaging techniques. Hyperspectral photos typically feature hundreds of thousands of narrower bands in the 10 to 20 nm range, whereas multispectral images typically have 3 to 10 bands[86].

Spectral indices: Over time, the scientific community has developed several spectral indexes to address challenging environmental or other issues. Vegetation indices are designed for quantitatively evaluating vegetative covers using spectral values. The satellite images are used to generate various spectral indices. The ability of vegetation indices to reflect light is dependent on their reflective qualities. The two most consistent regions of a plant's spectral reflectance curve serve as the foundation for the majority of vegetation index computations. Following are some of the vegetation indices available in the literature [87-89].

In agriculture, NDVI is used to characterize vegetation density and to help farmers forecast field productivity by evaluating weed and disease presence, growth, and germination rates. Green matter satellite imagery creates the exponential index. Green matter reflects near-infrared electromagnetic wavelengths while absorbing visible red electromagnetic waves. Chlorophyll absorbs solar energy most heavily in the red region of the spectrum (0.62 to 0.75 m), whereas leaf cellular structures reflect the most energy in the near-infrared range (0.75 to 1.3 m). Lower values of the reflection coefficient in the red region of the spectrum and greater values in the near-infrared region are produced by the increased photosynthetic activity. The ratio of these markers makes it possible to distinguish clearly between plants and other natural items We can identify locations that require fertilizer or crop protection goods through a thorough spectral analysis. Except when vegetation is scarce and high Leaf Area Index (LAI) levels might become saturated with dense vegetation, this index is only moderately responsive to changes in soil and atmospheric backdrop. It has been found that chlorophyll in particular and pigments that absorb radiation in the red region of the electromagnetic spectrum are more sensitive to the NDVI. Plants and non-plants, healthy plants and sick plants can be distinguished using NDVI. The enhanced vegetation index seeks to raise NDVI by enhancing the vegetation signal in areas with a high Leaf Area Index (LAI). The atmospheric effects like aerosol scattering by using blue reflection zones to rectify background ground signals will be reduced by the index. The Green Normalized Vegetation Index is similar to the NDVI, except instead of measuring the red spectrum, it measures the green spectrum over the range of 0.54 to 0.57 microns. This is a sign of how actively the vegetative cover is photosynthesizing. It is most frequently used to analyze multispectral data lacking an extreme red channel to determine the amount of water and nitrogen present in plant leaves and unlike the NDVI index, it is more sensitive to chlorophyll concentration.

Remote sensing image pre-processing: Preprocessing operations are used for correcting the distorted image and creating a better representation of the image data. In the real sense preprocessing refers to radiometric and geometric correction of remotely sensed data. Various preprocessing methods suitable for remote sensing data are given in the research articles [90-92].

Image Registration: Taking two multi-sensor or multi-temporal or multi-resolution images and overlaying them by aligning them geometrically is considered image registration for remote sensing. This is an important image preprocessing step.

Image classification techniques: The pixels of the remotely sensed image are classified and a specific set of labels or themes are assigned to each class. This process is called image classification. As the spectral reflectance and the reflectance properties of different feature types on the earth's surface are different, their recognition can be done through the classification process [93]. Object-based supervised and unsupervised image classification are the three types of image classification techniques used in remote sensing. The first two techniques rely on pixels.

Unsupervised Classification: Unsupervised classification aims to automatically separate remotely detected image pixels into classes with similar spectral characteristics. This approach of creating classes of pixels based on their common spectral signature is called clustering. K- Means, spectral clustering, fuzzy C-means, reinforcement learning, and ISODATA are the commonly used algorithms for image clustering. After creating the unclassified clusters the land cover classes are assigned to each cluster. Various unsupervised techniques used for the classification of satellite imagery are implemented and discussed in [94].

Supervised Classification: In supervised classification, images are classified based on selected training samples. First, a training area is identified for each land cover class. A signature file is created by selecting training samples for each class and then including all of these samples. To perform classification as the final step, one should use one of the supervised classification methods. Maximum likelihood (ML), iso clusters, class probabilities, principal components, SVM, logistic regression, and decision trees are all examples of classifiers with the shortest distance to the mean. In [95] Data from the Landsat5 Thematic Mapper is subjected to Markov random field, support vector machine, and maximum likelihood classification techniques.

Object-Based Image Analysis (OBIA): In this type of picture categorization, pixels are organized into standardized vector shapes with size and geometry. The various methods used to classify objects in this technique are shape, texture, and spectral. Remotely sensed imagery is classified into meaningful image objects and is assessed by analyzing the spatial, spectral, and temporal aspects. Various object-based methods are developed using readily usable objects from remotely sensed imagery by combining spectral and contextual information. The sequence of steps involved in OBIA includes segmentation, feature selection, training phase, validation phase, and classification. A review of the various such methods is available in [96].

Accuracy Assessment: An essential part of this process is calculating classification accuracy. For accuracy evaluation in supervised classification, ground truth data are needed. A previously classified reference map also can be used for assessing accuracy. The most popular method for evaluating the precision of LULC classification is the confusion matrix. Such an error matrix can be used to calculate accuracy based on ground truth data and other factors including classification scheme, sampling type, spatial autocorrelation, and size and unit of the sample. While calculating the overall accuracy confusion matrix can also be used for calculating the kappa statistics. Kappa statistics gives the estimate of how the results of classification compared to the values that are allotted by chance [97].

8. CURRENT STATUS & NEW RELATED ISSUES :

Earlier approaches to remotely sensed image interpretation depend on low and medium-level feature extraction techniques and representation. Such strategies have utilized various function and machine learning technique combinations. Small image data sets were used in these earlier methods. Deep learning models are increasingly being used for analyzing remotely sensed pictures. When compared to employing only one deep learning model, many hybrid deep learning approaches have produced significantly better outcomes. Deep learning techniques are used to classify land use and land cover with the help of multispectral and hyperspectral images. The preprocessing and postprocessing procedures boost classification performance. The classifier in deep learning automatically picks up new features. End-to-end Deep Learning models which have direct applicability to new data are often used in the remote sensing community [98].

For supervised techniques to provide useful results, the data must be properly labeled and there must be a significant number of training samples. For such supervised techniques, gathering ground truth is time-consuming and difficult. SVM is a popular classifier that works better with less number of training examples. Among the supervised classification methods, the minimum distance to mean algorithm avoids the presence of variability within a class and the shape and size of the clusters are not important in this approach. The maximum likelihood classifier is found to have a complex calculation of the probability that unknown pixels belong to a particular class. Random forest classifier is the popular algorithm in the remote sensing community which gives faster and more reliable classification. Support vector machine is has shown better performance than other classifiers and suited for a large number of input layers and different data sets such as hyperspectral images. Compared to SVM and Decision Trees, Artificial neural networks have given better results in many specific applications of LULC classification [99].

Table 3 provides an analysis of the major methods and technologies used in the articles collected for this literature review.

Table 3: Analysis of different land use classification methods

Reference No.	Year	Classification Algorithm/ method	Application objective	Observations and analysis
[11]	2022	Preclassification: image differencing, image rationing, NDVI difference, Principal component image difference. Post classification: Maximum likelihood, Support vector machine.	Tropical wetland management.	Multi-spectral satellite image analysis. Support vector machine has shown better accuracy among post-classification methods.
[12]	2020	SVM, Artificial Neural Network, Random Forest, Spectral angle mapper, Mahalanobis distance, Fuzzy ARTmap	LULC modeling of the built-up area, aquatic body, and agricultural and forestry land.	Validation of LULC using the spectral indices NDWI, NDBI, and NDVI. Better accuracy is observed with Random Forest.
[13]	2022	Deep Transfer Learning Resnet50V2, VGG-19, and Inception-V3	LULC categorization for making decisions and plans in rural and concrete areas.	Overfitting is reduced by dropout and early stopping in the training. A multiclass entropy loss activation function is used.
[14]	2020	Maximum Likelihood Classifier	Impact of Land surface temperature on conversion from vegetated into non-vegetated areas.	Normalized Ratio Urban Index is derived from Landsat multi-sensor data and used with regular spectral indices for classification.
[15]	2020	Maximum likelihood classifier	LULC map of Kashmir valley for some time.	Time series analysis for studying the changes in LULC classes. Geographic zones could be analyzed for studying the distribution of crop plants.
[16]	2017	Decision tree which is based on the CRUISE algorithm	Urban surface heat island analysis in Shanghai (China)	The statistical decision tree method is used. The accuracy is found to be 85.59%, 83.20%, and 88.14% for the years 2002, 2009, and 2013 respectively.
[22]	2022	Convolutional Neural Network	Crop classification	This object-based approach improves classification accuracy by using multitemporal images rather than single-data images.
[29]	2020	Deep Neural Network for pixel-wise labeling of images.	Automatic building extraction from	A noise-adaptive neural network for Convolutional Neural Networks reduces the

			aerial or satellite images.	manual effort required in annotation and object extraction tasks.
[30]	2022	A convolutional neural network with a hidden Markov model based on a stacking ensemble learning approach.	Image classification of remote sensing scenes	The Hidden Markov model is used to find contextual information about extracted features across sample images.

9. IDEAL SOLUTION, DESIRED STATUS & IMPROVEMENTS REQUIRED :

For preprocessing, picture categorization, and change detection, many techniques have been employed and are available in the literature. This study looks into pre-processing, after classification change analysis, comparison analysis, and calculation of accuracy. To find out more about the kind of vegetation present and the state of crops, rangelands, woods, etc., it is possible to assess the spectral characteristics of vegetation in various parts of the spectrum. These spatial data are then captured, stored, manipulated, analyzed, and managed in a GIS system. Deep learning techniques with OBIA can be further explored and implemented for developing an accurate classification model. The shape of the objects is an important property in OBIA that can improve classification accuracy.

10. RESEARCH GAP :

The literature review reveals that various Machine Learning algorithms are applied to satellite or aerial images for LULC classification. In the later stage, the change detection techniques are used for quantifying the changes in LULC.
Research Gap 1: Scope for advancement in the usability and accuracy of mapping systems.
Research Gap 2: Optimal vegetation index suitable for the selected area of interest can be calculated.
Research Gap 3: Classification models can be fine-tuned with hyperparameters.

11. RESEARCH AGENDA BASED ON RESEARCH GAP :

(1) How to perform remote sensing data acquisition?
(2) What are the preprocessing methods suitable for remote sensing data?
(3) Which machine learning algorithm gives optimal results in developing an image classification model?
(4) How to improve the classification accuracy?
(5) How to generate an agriculture land use map?
(6) How to perform visual and quantitative change detection analysis?

12. ANALYSIS OF RESEARCH AGENDA :

By analyzing scientific and applied research work on mapping the study region, a technical system for the development of agricultural electronic maps employing GIS and technology can be built. The initial collection of spatial data, software selection, preprocessing, creation of layers into themes, conditional character processing, printing, and other steps involved in creating agricultural maps are all part of this technical system.

13. FINAL RESEARCH PROPOSAL/PROBLEM IN CHOSEN TOPIC :

(1) Retrieving, preprocessing, and analyzing data captured from the satellite.
(2) Mapping the identified location according to the study purpose.
(3) To use object-based remote sensing change detection technique and track the differences in vegetation area before and after.

14. ABCD RESEARCH PROPOSAL ANALYSIS :

The research process requires following a series of steps completed systematically and the DDLR model presented in [100] gives focusses on the flow of the research process and helps design a research methodology that is reliable and robust. The framework for analyzing the business strategies and models is studied in [101] and a qualitative analysis called ABCD analysis is presented and compared with other techniques such as SWOC, CPM analysis, etc. The authors of [102] have covered how ABCD analysis can be applied as a research methodology in firm case analysis methods. SWOC analysis is used to identify a product's advantages, disadvantages, opportunities, and challenges. The authors of [103] have reviewed and applied SWOC analysis for higher education institutions. ABCD analysis is also applicable for determining the potential of the research methodology designed to carry out research in a particular area.

Advantages:

(i) Helps in environmental modeling to study the changes that are happening in our ecosystem.
(ii) Possible to get overall information on vegetation growth situation over a large geographic area in almost real-time
(iii) Availability of GIS data sets

Benefits:

(i) Government agencies can carry out surveys more effectively by mapping changes in land use and land cover at the regional level.
(ii) Land cover identification provides the basis for carrying out monitoring activities.
(iii) Change detection **c**an be used in vegetation monitoring**.**

Constraints:

(i) Classification accuracy assessment
(ii) Data consistency
(iii) Lack of past ground truth data

Disadvantages:

(i) Change detection accuracy depends on classification accuracy, which in turn depends on image quality.
(ii) Change detection is more difficult and time-consuming if performed after classification.
(iii) Choosing appropriate thresholds to recognize the areas that have changed is difficult.

15. SUGGESTIONS TO IMPLEMENT RESEARCH ACTIVITIES ACCORDING TO THE PROPOSAL :

The various algorithms used in change detection which are identified in this study will be implemented initially with the remotely sensed images collected for the study. Based on the suitability of the approach for the selected region of interest, the algorithm will be identified and extended with finetuning to get accurate results. The images would be collected using earth explorer and ArcGIS tool will be used for performing analysis.

16. LIMITATIONS OF THE PROPOSAL :

The research proposal given in this study gives a broad overview of how remote sensing data might be utilized to map areas to forecast future circumstances to detect change. The actual study location and the specific crop that will be used for monitoring change are not revealed in this proposal.

17. CONCLUSION :

Remote sensing data are effectively used in various applications of GIS. This study explores different methods of land use analysis and focuses on identifying the most up-to-date approaches suitable for further research in the selected area. This study has also explored the significance of LULC concerning various applications. The efficiencies of various methods available in the literature are analyzed based on the results given in the research papers. The research challenges in this area are identified and this helps in framing the research questions. Agriculture observation and monitoring are important activities in agriculture. This study helps in identifying a research problem related to time series analysis for analyzing what is occurring within a set distance of a feature using LULC change detection method.

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