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Analysing The Effectiveness of Machine Learning Algorithms for Land Use Land Cover Classification

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Abstract: Accurate and reliable information about land use and land cover is very important for change detection and monitoring of specific area. Land use and land cover (LULC) dynamics play an important role in environmental planning, resource management, and sustainable development. It is also useful in updating the geographical information about specified area. With the advent of remote sensing technology and the accessibility of large-scale datasets, machine learning algorithms have emerged as powerful tools for analyzing and predicting LULC changes. This paper gives a comprehensive review of the application of machine learning algorithms for LULC dynamics. It discusses various algorithms, data sources, and methodologies used in the field, highlighting their strengths and limitations. The review also identifies key challenges and future research directions to enhance the effectiveness of machine learning in LULC analysis.

Keywords: Land use • Land cover • Machine Learning • Remote Sensing • Geographic Information System.

Introduction

Classification of human activity and natural components in landscapes over time is called LULC and is dependent upon established scientific, statistical methods for examining relevant source data. Earth observation is concerned with the gathering of information about the biophysical systems on the earth's ground surface, observing and modeling interactions of earth's ground 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 (Usmani et al., 2020; Holdstock et al., 1998). 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 areas as mapping land use land cover, forestry, faring, urban planning, geomorphological surveying, etc (Mason & Schmetz, 1992). 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 (Evangelista et al., 2009; Morisette et al., 2006). Precision agriculture involves the application of such advanced techniques and attempts to improve agriculture production by optimizing agricultural inputs (Sishodia et al., 2020). Various application-specific approaches are available in the literature for designing optimal vegetation indices (Verstraete & Pinty, 1996; Ceccato et al., 2002; Huang et al., 2014).

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.

Objectives

The main aim of this review study 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 implemented foe land use land cover study with use of remote

sensing data.

(2) To analyze land use land cover mapping and change detection.

(3) To study image classification methods used in remote sensing.

(4) To study the current status and analyze the existing approaches.

Methodology

Remote sensing images will be collected using Earth Explorer which is a free open browser platform for downloading aerial or Landsat 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.

Review of literature/ Related works:

Various models and comparative studies of different approaches are available in the literature. The related research articles are collected and used for presenting the research evidence. 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 LULC analysis.

SN	Area ofStudy	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.	(F. Malandra et al., 2018)
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.	(Márquez-Romance et al., 2022)
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.	(Talukdar et al. , 2020)
4	Deep learning approaches for LULC classification.	Using pre-trained deep learning models using remote sensing images and improving the outcome of LULC classification.	Deep Transfer Learning Models namely Resnet50V2, Inception-V3, and VGG-19 are used for classification. The selected hyper parameters were adjusted for improving the classification accuracy.	(A. Alem & S. Kumar., 2022).

SN	Area ofStudy	Focus	Outcome	References
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.	(Piyoosh A. K. & Ghosh, S. K. ,2022)
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.	(Alam, A. et al., 2020)
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 help 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 CRUISEalgorithm.	(Wang, H. et al. , 2017)
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)
	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.	
9	Analysis of various change detection methods	Examining the basic procedures needed for detecting changes and emphasizing the difficulties and problems encountered in thisarea.	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 methodssuch as fuzzy, neural networks, transforms, and algebra-based approaches.	(Asokan, A et al., 2019)
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.	(Asokan,A. et al. , 2020)

Remote sensing image processing techniques are mostly used in tackling various applications and have a remarkable 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

SN	Area of Study	Focus	Outcome	References
1	Remote sensing data acquisition methods	Study of the effect of using data capturing methods on automatic changedetection.	This research provides information on the effects of various remote sensors, 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	(Goswami, A *et al.*, 2022)

SN	Area of Study	Focus	Outcome	References
			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.	(Zhang, X., 2022)
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).	(Li, H. et al., 2022).
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.	(Paul, S., & Pati, U. C, 2021)
5	Feature reduction technique based on PCA.	Classification of Hyperspectral remote sensing image and dimensionality detection.	Several feature reduction algorithms based on PCA, including FPCA, SPCA, 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.	(Uddin, M. P. et al., 2021)
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.	(Alshari, E. A., & Gawali, B. W. 2021)
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.	(Soubry, I., et al., 2021)
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.	(Roy, B., et al., 2021)

SN	Area of Study	Focus	Outcome	References
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.	(Wiatkowska, B., et al., 2021)
10	Deep neura 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.	(Zhang, Z. et al. , 2020)
11	Classification of remote sensing sceneimages.	Building Self-compensation convolution neura network (SCCNN) for better performance.	By using fewer filters, this method lowers the temporal complexity of theconvolutional neural network, and the convolutional channels are compensated by the input features.	(Cheng, X. & Lei, H. , 2022)

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 (Gong, M. et al., 2017) have provided a framework for detecting the change in multispectral remote sensing imagery. Temporal characteristics are retrieved from super pixels and an object-based deep learning model is presented in (Lv, N. et al., 2018). By inventing a change detection method for multi-temporal hyperspectral pictures, the authors of (Du, B. et al., 2019) have showed the importance of deep neural networks (Mou, L. et al., 2018). The post-processing approach is proposed in (Lv, Z. et al., 2018) for improving the output of the detection of land cover change. The Normalized Difference Vegetation Index (NDVI) and the Normalized Burn Ratio (NBR) are employed in (Housman, I. et al., 2018) as forest greenness indicators for the proposed algorithms of basic z-score, harmonic z-score, and linear trend, which are implemented to discover changes in the condition of the forest. Examination of various 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 (Kwan, C. et al., 2019). The proposal in (Zanotta, D. et al., 2015) models replicated changes in the source domain by defining decision rules for the target domain image pair. (Wang, B. et al., 2015) shows a change detection method that is unsupervised and cross- sharpening of multi-temporal images combining the intercept, slope, and correlation indexes, and image segmentation concepts are executed to reduce detection errors due to spatial displacement with images having different acquisition angles. In (Zhang, H. et al., 2016) the spectral channels are modified into feature space for reducing redundancy and avoiding noise (Singh, A., 1989).

The three main techniques for change detection after categorization are picture subtraction, image ratio, and change detection (Shaoqing, Z. & Lu, X., 2008). The article (Ben Abbes, A. et al., 2018) analyze the effectiveness of the multiresolution analytical wavelet transform method with additive seasons and trends (BFAST). PCA is implemented for identifying the set of metrics of Landscape Analysis and to study spatiotemporal urban dynamics (Vanjare, A. et al., 2014; Forkuo, E. K. & Frimpong, A., 2012; Sahani, S. & Raghavaswamy, V., 2018). Another approach has used a regression model to study the negative effects of urban expansion (Tavares, P. et al., 2019; Lyu, R. et al., 2018). 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 (ED Chaves, M. et al., 2020; Xiao, J. et al., 2018). High spatial resolution aerial images of Earth are used in the proposed work in. Multi sensor multi temporal satellite imagery is implemented for change detection utilizing Principal Component Analysis(PCA) in showing precise outputs.

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. It is measured how much electromagnetic radiation makes up the energy that is dispersed back. The fusion of various types of remote sensing data with supplementary data from various sources is the driving force behind several new scientific research.

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.

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. Following are some of the vegetation indices available in the literature.

Remote sensing image pre-processing: Preprocessing operations are used for correcting the distorted image and creating a better representation of the image data. Various preprocessing methods suitable for remote sensing data are given in the research articles.

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.

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. Various unsupervised techniques used for the classification of satellite imagery are implemented and discussed in.

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.

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.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.

Accuracy Assessment: An essential part of this process is calculating classification accuracy. For accuracy evaluation in supervised classification, ground truth data are needed. The most popular method for evaluating the precision of LULC classification is the confusion matrix. 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.

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. End-to-end Deep Learning models which have direct applicability to new data are often used in the remote sensing community.

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. Random forest classifier is the popular algorithm in the remote sensing community which gives faster and more reliable classification. Compared to SVM and Decision Trees, Artificial neural networks have given better results in many specific applications of LULC classification .

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?

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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