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Land Cover Mapping Using Remote Sensing Data

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Abstract Land cover is a complex parameter because it represents the relationship between socio-economic activities and regional environmental changes, which is why it is important to review and update it periodically. This paper seeks to navigate via a range of subtopics on Land Cover Mapping (LCM) using Remote Sensing (RS) technology for providing enough information that play a significant and prime role in planning, management and monitoring programmes at local, regional and national levels. The literature review structure is described as; give a review of information type and sources with highlights on the strengths and weaknesses of distinct RS information as well as distinct variables extracting from RS information that have been used for LCM. Similarly, the highpoint was done on the LCM techniques which comprise conventional and remote sensed techniques for accurate LCM. For detailed knowledge of the methods, phases, and algorithms of Image classification (IC) for LCM, a brief overview is provided and some issues that influence the efficiency and accuracy of the IC methods were also discussed. From this investigated literature, the most common RS data used for LCM are multispectral, hyperspectral, light detection and ranging (LiDAR), and radio detection and ranging (radar). The choice of appropriate RS data for LCM, however, relies on data accessibility and the particular goal to be obtained and type of classification algorithms. Non-parametric classification algorithms tend to be superior to parametric classification algorithms in LCM using RS data. Nevertheless, the issue which non-parametric algorithms are better than other LCM algorithms was not normally answered. As conclusion, LCM efficiency is influenced by numerous variables like landscape, sampling schedule, training selection techniques and training size, type of non-parametric algorithms, raw data, etc. Thus, these influenced variables need to be addressed before LCM using RS data.

Keywords Land cover mapping techniques, Image classification process, Remote sensing data

1. Introduction

Land cover (LC) is an influential factor in geographical research, from physical geography observations to environmental science and spatial planning techniques [1]. It is a dynamic parameter because it represents the relationship between socio-economic activities and regional environmental changes, which is why it is important to review it periodically. The study of LCM and the identification of changes are very relevant for the proper planning and use and management of natural resources [2]. Traditional approaches include collecting demographic data, LC feature censuses and surveys for LCM are not suitable typically in multi-complex environmental research areas. There are many problems that frequently occur in these research areas and the difficulty of multi-disciplinary data set management with new technologies such as satellite RS and Geographic Information Systems (GISs) have frequently been utilized to overcome the problems. Such technologies generate information for the analysis, visualization, and monitoring of the dynamics of land cover for environmental management. LCM using RS requires clarity and details that will make it easier for learners to get enough information on this subject to begin any project. Therefore, the point of this article is to navigate via a range of subtopics of LCM using RS. The remaining of this article is split into five sections: first section refers to fundamental of LCM followed by RS data types and sources, whereas land mapping techniques denotes in third section. While, the imager classification analysis and methods and factors influencing LCM are described in sections four and five respectively.

2. Fundamentals of Land Cover Mapping

2.1. LCM Definition

Remote sensing (RS) is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft) [3]. Remote sensors collect data by detecting the energy that is reflected from Earth. These sensors can be on satellites or mounted on

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aircraft [1]. Remote sensors can be either passive or active. Passive sensors respond to external stimuli. They record natural energy that is reflected or emitted from the Earth's surface. The most common source of radiation detected by passive sensors is reflected sunlight. In contrast, active sensors use internal stimuli to collect data about Earth. For example, a laser-beam remote sensing system projects a laser onto the surface of Earth and measures the time that it takes for the laser to reflect back to its sensor.

In most of LCM studies, the researchers are combining the both terms land cover and land use as land cover in which natural and semi-natural vegetation is marked with land cover and agricultural and urban regions concerning land use [4]. These are two distinct differences, indeed, and issues between land cover and land use are basic since they are generally ignored or forgotten. Ambiguity and confusion among these two concepts lead to practical issues, particularly when information from both sensors must be matched, compared and/or coupled for LCM. (LCM). *Land cover* LC is distinct as "type of function found on the earth's surface" (e.g., forest, water, asphalt), while the word is running *land use* is "connected to human activity or financial function" (e.g., forestry or residential areas) [5]. LCM is the forms of land use and land cover characterize the earth's surface at any demanded scale. Frequently, Land Cover Mapping (LCM) is used as a group word, suggesting either a map or a combination of both kinds; land cover and land use [6].

2.2. Importance of LCM

LCM is a basic variable that impacts and links several components of human and physical settings as it can offer important knowledge to understand the dynamics of the Earth, such as climate change, preservation of biodiversity and interaction around social activities and terrestrial changes. [7,8]. LCM studies are multidisciplinary in nature and therefore respondents are varied and diverse, varying from global wildlife and conservation foundations to public scientists and forestry firms [9].

Regional government organizations have an operational want for tracking LCM and land cover, as managing the Natural resources of their corresponding areas is within their authority. Besides enabling sustainable land management, data on land cover and land use can be used to plan, monitor and evaluate production, industrial activity or reclaim [7-9]. Identification of long-term land cover modifications may show a reaction to a change in local or regional climate circumstances, the basis of worldwide terrestrial surveillance. Environmental surveillance scientists, conservation officials and municipal affairs departments will examine variations in land cover, with interests ranging from tax assessments to vegetation recognition mapping [10]. Governments are indeed worried about the overall protection of domestic assets and are engaged in publicly delicate land-use conflict operations. In certain areas all across the globe, the absence of understanding about LCM and its dynamics could be ascribed to: (1) weak public support for mapping organizations and research organizations, (2) costly software and equipment, (3) inadequate budget distributions for information acquisitions and (4) opposition to modifications, particularly by traditionalists in the mapping domain [11].

3. Data Type and Source for LCM

Different data have been used for LCM and can be clustered into:

3.1. Ground-Based Data

LCM from in-situ or ground-based data using various in-situ techniques or ground-based surveys, which are systematic data collection and data to provide extensive data on LC's status and dynamics for strategic and planning purposes. [12]. These data could be gathered for several purposes, such as surveillance, modeling, predicting multiple biophysical procedures, dangers, and fire risks, so they are generally applied on multiple scales to achieve distinct LCMs [13]. However, Ground-based data has some spatial, attribution and temporal limitations, the use of LCM ground-based records is not completely dismissed and more information can be found in [12,14,15].

3.2. Remote Sensing-Based Data

Detectors installed on satellites or aircraft obtain radiation and/or deliver it to the earth [7]. The distinction in quantity and wavelength of the reflected energy among features or phenomena being investigated provides the feature and its spectral signature facilitates to differentiate among distinct kinds of land use, vegetation, soil, etc. RS technology has thus get to be relevant information for assessing LCM's historical and current phase and possible future trends [16-18]. This data is generally collected through RS satellites and then used to graph LC characteristics on small to large spatial scales. It replaces traditional techniques of data gathering, involving time and expense-intensive ground surveys and reducing the difficulty of field work [5, 19, 20]. According to [2], "The primary benefit of RS data over various types of conventional data collection is the ability to supervise big worldwide ground regions without any need for ground-level investigations, in comparison, the inspection method is less expensive than lengthy-term ground and large-scale LCM investigations". Such data are primarily in digital form, which is then performed by a computer to process bigger quantities of records and lower the price of RS data and collective purchase and land-use orders [7]. The growing accessibility of cheap or free data records, the steady fall in hardware and software costs and increased knowledge of the prospective opportunities of RS innovation include the necessary impetus for LCM in non-developing nations. [21]. With a the rapid evolution of RS technologies, such as multispectral, hyperspectral, light detection and ranging (LiDAR), and radio detection and ranging (radar) can be used to fill ground-based data constraints, contributing to up-to-date LCM on different levels mainly by incorporating ground databases with advanced RS data [12].

3.3. Major Remote Sensing Sensors for LCM

The LCM's primary remote devices are lumped into three groupings; High Spatial Resolution Sensors (HSRS), Medium Spatial Resolution Sensors (MSRS) and Coarse Spatial Resolution Sensors (CSRS). Each of these groups has its own pros and cons in aspects of spatial and time resolutions, expenditure and time of acquisition [5]. For example, HSRS such as Quickbird-2, IKONOS-2, and Spot 4 and 5 have elevated resolutions of space (0.61-20 m) and time (1-3.5 days). The temporary resolution is, even so, for future information or data required. For the resolution of 1-3, 5 days, historical data for a region might not be accessible, for if data is not demanded, this will not be retrieved. In addition, these instruments cannot have heat bands and are therefore incapable of giving surface temperature mapping data utilizing an energy equilibrium technique. These data are primarily used for LCM at local level [22].

The MSRS (15-120 m), such as Advanced Spaceborn Thermal Emission and Reflection Radiometer (ASTER), Advanced Land Imager (ALI), Landsats, and Sentinel cannot provide a large temporal resolution; its temporal resolution exceeds 16 days. Landsat and Sentinel data are presently free of charge are used regularly for regional or national output LCM [23]. Many regional LCM programs have been implemented using MSRS data for creating single-date regional LC maps (e.g. EOSD 2000 in Canada; CORINE LC 2000 in Europe), with Landsat obtained remarks within the target interval year (e.g. ±1–3 years). While, the programs like U.S. NLCD 2001/2006/2011; Australian NCAS-LCCP) or even frequently for certain types of LC (e.g. Brazilian PRODES) used MSRS data to perform the LCM continuously and permit LCM and evaluation of changes [14].

The CSRS data has a frequency of one or two days and a spatial resolution of 250-1000 m hence the data is free and covers further bands than most other satellites (altogether of 36 bands) [8]. Commonly, CSRS uses multi-year information from Landsat, AVHRR, SPOT-Vegetation, ENVISAT MERIS, and Terra / Aqua MODIS for worldwide LCM with total accuracies varying from 65% to 80% [5,24,25]. All these sensors are accessible as raw data as well as processed data form. These data applied by using classification techniques to generate specific LCM products either directly or indirectly using raw data and processed data [7].

3.4. RS Feature Extraction and Feature Selection

RS data, as mentioned above, have several different characteristics of spatial, spectral, radiometric, temporal, and polarization. In the original space, band spectral values are used as an input in the LCM or classification process [7]. The benefit of utilizing original space is the use of spectral data straight and the extraction phase also does not seem to be featured. Feature space is acquired through techniques of extraction of features that convert data from original space into feature space. The benefit of using feature space is the ability to enhance classification efficiency in certain classification methods. [26]. Several features extraction techniques can be used to covert RS data (e.g. Principle Component Analysis (PCA), Minimum Noise Fraction (MNF), Transform Discriminant Analysis (TDA), Decision Boundary (DP), Feature Extraction (FE), Nonparametric Weighted Feature Extraction (NPWFE), Wavelet Transform (WT) And Spectral Mixture Analysis (SMA)) [27].

RS data's inclusive characteristics can be regarded into five groups. Spatial information is the first class. The HSRS offers more comprehensive earth's ground spatial information to data. However, the convenience of their high costs barricades information restricted their use. The freely available MSRS pictures are indeed the primary source of information for LCM. The second category is spectral information or data about the spectrum. Variations among spectral signatures are used to assist classify RS pictures into landscape feature groups because distinct feature spectral signatures have distinct forms. Hyperspectral data have adjacent small wavelength bands (approximately 10 nm per band) and are capable of capturing much more accurate spectral signatures than multispectral detectors (approximately 100 nm per band). Temporal information is the third category [28]. Accurate and timely data defining the nature and extent of the earth's surface and its times over time is vital to the production of better LCM [29]. The fourth category is angular information. Study’s findings have shown that data on bidirectional reflectance distribution (BRDF) can also be used to supplement spectral signatures in order to generate LCM [30]. The fifth category is topographic information or data used as input in LCM process. In [22], it was observed that perhaps the combination of topographical altitudes and slopes in the LCM assessment method could decrease misclassification of various LC classes in mountainous regions, thereby improving LCM. Such variables were utilized directly or indirectly or as multi-source RS data in the LCM classification method on a national and regional scale, but nonetheless, prevalent spectral signatures used during IC process [28,31]. Not many of these features of inputs are frequently similarly comprehensive. Some of them over the particular assignment may be obsolete, noisy, meaningless, associated or irrelevant. Logically, any classification technique should also include just those features that directly contribute, leading to increased LCM outcomes [28]. Under this situation, the purpose of Feature Selection (FS) is to pick a subset of RS data features or characteristics appropriate to a particular issue.

The selection of an appropriate RS features as input is crucial, the addition of variables other than the original spectral bands can significantly influence the performance of IC thus LCM. So FS techniques may be used for this purpose. FS techniques split into two groups; FS based on statistical feature data and FS based on classification techniques [32]. The latter, FS based on statistical criteria, defines an ideal subset of features unbiased of the classification process. The latter eliminates or chooses the most appropriate characteristics on the premise of particular criteria [32]. The most widely used FS techniques of choice of features are Feature Space Optimization (FSO), Optimum Index Factor (OIF) algorithm, Bhattacharyya distance, RF-feature selection, DT, Jeffries–Matusita (JM) distance, RF, CART, Correlation-Based Feature Selection (CFS), Wrapper, Graphic Analysis Statistical Methods and Fuzzy-Logic Expert System [33]. Furthermore, manually FS method [34] and non-parametric classification techniques like SVMs or NNs [28] can be used for features selection process for better LCM. More information on the choice of important features and methods can be found in [28,33].

4. LCM Techniques

Approaches for LCM are divided into traditional and RS methods.

4.1. Traditional Techniques

Using destructive technique or field survey as a common method for the traditional techniques and often used for LCM. Theoretically, field surveys are regarded as the optimal approach to accurate LCM per unit region and are only used routinely to validate other techniques [7,35]. Traditional LCM techniques are extremely labour-intensive, expensive techniques, less aggressive, work-consuming, occasionally inadmissible owing to bad accessibility, and hard to enforce in regional regions [22]. Numerous writers in this sector do not completely reject the use of traditional techniques for the LCM, incorporating them with contemporary RS techniques would significantly boost future use or renew maps and significantly improve LCM.

4.2. Remote Sensing-Based Techniques

The RS technique is the task of extracting LC details by analysing RS data based on components of description such as colour, texture, shape and association details, etc. [22,36]. Various techniques can be categorized widely either as monitored or as unsupervised relying on whether or not real ground information is included as references data. There was an increased interest in using remotely sensed-base techniques in the late twentieth century to provide effective and succinct LC maps on different levels. As of RS data with the high spatiotemporal resolution, fine geometric resolution, broad coverage and timely updates are becoming a significant data source that has been the only achievable method of obtaining LC information over vast regions at a reasonable price and appropriate accuracy owing to repetitive data collection at the workable effort. [37,38]. The level of accuracy and efficiency of RS techniques, nevertheless, relies on the sensor's capacity to characterize LC's spatial heterogeneity with negligible error [39-41].

5. Image Classification Process and Techniques

5.1. Image Classification Stages

Image Classification (IC) The technique involves transforming statistical spectral measurements into a set of significant classes or labels consisting of describing a landscape. [42]. According to [21], IC can be done whether visually or digitally using a single picture dataset, various images obtained at separate moments, or image data with extra information such as values of altitude, or specialist understanding of the region. Traditionally, LC classification Multiple paths are involved premised on remotely sensed data [5], *(i) "Feature extraction*: The term feature refers to a single element of a pattern. RS information is most often extremely linked between spectral bands, which might not be helpful in classifying LC and may decrease the accuracy of classification. Thus, extraction of the function performs two functions: (1) Separation of valuable information from noise or non-information and (2) Dimensionality reduction of data with a view to simplifying the calculations conducted by the classifier and increasing the effectiveness of statistical estimators in the statistical classification.

By employing spatial or spectral transformation to the illustration, these objectives can be accomplished. This phase is additional when classifying remotely sensed images, i.e. if required, pictures can be used immediately. *(ii) Training:* The term “training” the result of many pattern recognition technologies were “trainable”; i.e., by modifying their parameters to a training pattern, they realized the discriminating features in the feature space (pixel vector) the real class of which is known. This training procedure for a classifier can either be supervised by the analyst or unsupervised. (iii) *Labelling*: It is regarded as the labeling method for allocating individual pixels with their most probable LC category.

5.2. Image Classification Techniques

IC approaches can be split into parametric and non-parametric methods centered on the classifier's use of certain distributional hypothesis about the data. For parametric methods, since there is a big range of methods available to classify images, such as MLC. Because this hypothesis is often breached, particularly when multi-source information is used, the parametric algorithms are sometimes criticized owing to the need for normal distribution. This restriction does not apply to nonparametric algorithms and has more benefits than conventional parametric classification techniques [42]. Since separate spectral data pieces or the conjunction of RS and ancillary data may be used, distinct non-parametric classification techniques have been implemented such as Random Forest (RF), Artificial Neural Network (ANN), Decision Tree, Fuzzy-set CTA Algorithm, Fuzzy Artmap, KNN, Object Base Classification, SVM and Expert Systems [43-45]. Several variables have to be addressed when selecting a classification technique for use, such as the RS spatial resolution data, classification scheme, and classification software accessibility [34,46].

5.3. Image Classification Accuracy and Uncertainty

LCM product accuracy assessment is always an essential element for data users. Sometimes this is not successfully carried out for massive-scale projects owing to the absence of reference details or project time constraints or financing [47,48]. A piece of autonomous and objective information set for the performance of the LCM item is crucial for an impartial evaluation. Base on the study [96], four requirements are defined; 1) likelihood sampling; 2) appropriate sample sizes to measure user accuracy with an appropriate level of accuracy; 3) cost-effectiveness; and 4) relative spatial distribution of samples around the region of concern [49]. The assessment of accuracy is often provided in an "error matrix", as designated by [50], the error matrix enables classification efficiency to be measured by analysing inclusion and omission failures, particularly where a small amount of LC classes are of concern.. The kappa statistics, or k-hat, are always an overall indicator of accuracy and are designed to address for the possibility of random contract [47,48,50]. An overall required graph accuracy of 85% is sometimes provided as a benchmark, but it might not be sustainable to attain [51,52]. Another technique of combining thematic maps is to create a confusion matrix which can be achieved from the error matrix components. Refer to [53] suggested tau index (T) as a metric of classification techniques accuracy in which it is estimated compared to class random pixel alignment.

Uncertainties in a classification operation at distinct phases affect the classification procedure and LCM [53,54]. Recognizing the interactions between certain classification phases, identifying the weakest connections in the image processing circuit and then dedicating attempts to improve them are vital to a good classification of images [53]. For instance, geometric adjudication or registration of images among multisource data may result in uncertainty of position, whereas techniques used to calibrate atmospheric or topographic impacts may generate radiometric mistakes. In study [55, 56] discovered that RS data contains have five categories of uncertainties: positional, support, parametric, structural (model) and variables. Uncertainty can be designed or calculated in numerous ways, such as fuzzy and deterministic classification methods, or through visualization (geo-visualization and interactive visualization) [55,56].

6. Factors Influencing LCM Accuracy

6.1. Heterogeneity of Study Area

Distinct landscapes have varying rates of heterogeneity and switches between LC kinds can be separate or fluid and difficult to assess even in the field, thereby affecting the precision of training data collection and ultimately affecting LCM accuracy. [57]. For instance, the spatial geometry of the landscape system can, however, influence the accuracy of the LCM [58] mentioned that there are reduced LCM accuracies in the research region with a greater rate of homogeneities like vegetation and forest features.

6.2. Remote Sensing Data Type

The choice of appropriate RS information for a particular purpose is the main essential step for a successful LCM system [59]. Seeing as various sensor information sources are now easily accessible, it is crucial to understand the positives and negatives of distinct kinds of sensor information for the choice of appropriate RS information. [45,60]. Landsat TM images, for instance, have a limited number of spectral bands with wide wavelengths, which can be hard to distinguish particular LC class on the surface of the Earth. On the other hand, hyperspectral images with a significant amount of bands and narrow wavelengths can strengthen the accuracy of classification [5], However, the big volume of data often produces IC processing dilemma [34]. Several previous literature evaluated the features of distinct RS information in spectral, radiometric, spatial and temporal resolutions [61]. The choice of RS information for LCM influences many variables such as the need of the applicant, the accessibility of varying RS information and their features, the cost and time limitations, the scale and features of a research region and the experience of the officer in using the RS information requested. Another significant factor affecting the assortment of RS information is the atmospheric situation. Frequent cloudy circumstances in the humid tropical areas often hinder the collection of high-quality optical sensor information [61]. Different forms of radar information thus operate as an significant additional source of information in this situation [15]. In order to evaluate the reliability of satellite data, such as [62] used sentinel-2B and Landsat 8 OLI data depending on object classification (OBIA) technique to classify mangrove land cover. Field sampling was performed using Unmanned Aerial Vehicle (UAV) at Liong River, Bengkalis, Riau Province. The outcome indicates that the overall accuracy classification utilizing Sentinel-2B was greater than Landsat 8 OLI imagery with a value of 78.7% versus 62.7% and slightly distinct 7.23%. In another research carried out by [63], sentinel-2 and Landsat 8 imagery used an object-based classification technique to generate LCM in a Mediterranean wetland region. The findings indicate that for most LC categories, an object-based classification using only Sentinel-2 and Landsat 8 image data, without band indexes or ancillary data, provides very comparable outcomes, the overall accuracy becoming about 87–88 percent with marginally better outcomes while using Sentinel-2. While using Sentinel-2 results in a rise in file size and processing times, the evaluation of certain LC classes shows an enhancement relative to Landsat 8, identifying more linear and tiny size components with a better distinction of picture characteristics in the categorized map. These advances should not, but, underestimate the importance of Landsat data in the future, as both satellites offer data of elevated accuracy so that they can and should co-exist and be used together just to increase the accessibility of data in order to achieve the best opportunities in RS research.

6.3. Data Pixel Size and Scale

Within the context of RS, the phrase "spatial resolution" is the capacity of the sensors to rectify landscape spatial details. Numerous studies showed reducing the accuracy of LCM with increased spatial resolution. [64]. In particular, satellite data with higher resolution get more pixels comprising compounds of cover types, rendering LCM harder [57]. Higher spatial resolution data might provide more thematic details, but perhaps the pixel size trade-off is usually covered by a tinier scene region, culminating in a possibly more complex and expensive LCM project. [64]. Chen et al. (2004) indicated that this rise in classification accuracy depends on the size and scale of the RS data or the scene geometric resolution. In reality, for higher resolution images, the advancement is greater. In a study conducted out by [65] used optical data obtained by two multiple sensors (15-m resolution THEOS and 30-m resolution Landsat 5-TM) were examined in 2010 against the ability to properly classify particular land cover classes at various extrapolation scales. The SVM classification is used and the study area was the district of Kathu, Phuket, Thailand. The land cover has been categorized as forest, built-up, highway, water, farming, pasture, and bare land into 7 groups. The outcome showed that THEOS ' general precision at 15 m was significantly greater than Landsat-5 TM at 30 m resolution (90.65% and 89.00% respectively). In another research carried out by [66] Optical information obtained by two inertial sensors (LISS IV with 5.8 m and Landsat 8-OLI with 30 m spatial resolution alternatively) were examined against the capacity to correctly classify into separate LC classes. Separability assessment was conducted to assess the performance of training specimens using the TD technique. In addition, the MLC was used to conduct the classification of LC. The results revealed that 83.28% overall accuracy and 0.805 Kappa coefficient for LISS IV image were noticed to be higher compared to 77.93% overall accuracy Landsat 8-OLI image and 0.742 overall Kappa coefficient.

6.4. RS Data Variables

Appropriate use of RS data characteristics or variables as input information (initial space or feature space) can enhance the precision of LCM in a classification process [67]. Another critical step for LCM is define the best suitable variables that are most valuable in separating LC features to decrease the dimensionality of data sets without scarifying accuracy and to reimburse for some frequent problems connected with RS data such as shadows and spectral variability within the same LC classes [46]. Thus, use of so many variables in the classification method may reduce the classification accuracy owing to distinct capacities in the separability of the LC class. [65,66,68]. Different studies analyse the impact of the type of feature on LCM [69]. In their research, a sequence of well-controlled LC classification studies using KNN and SVM classifiers methods on a Landsat 8 OLI image assessed the impacts of the neighbouring area characteristics and the various characteristic set settings on enhancing the LC classification. When adding the adjacent region characteristics, both classifiers produced overall accuracy was greater than when using only spectral characteristics. The overall accuracies of the LCM were 85.45% and 88.87% including both for the KNN and SVM classifiers using only spectral features, and the accuracies were enhanced to 94.52% and 96.97% respectively as well as the increased classification accuracy among all kinds of LC.

6.5. Data Pre-processing

As of atmosphere, solar lighting angles, topography and sensor viewing angles simplify the classification method and can reduce the accuracy of the classification [70]. Range of pre-processing procedures has been created to retrieve data altered by atmospheric and radiometric impacts, including geometric rectification or image registration, radiometric calibration, atmospheric correction, topographic correction, detection and restoration of poor lines, image improvement and masking. The pre-processing of RS information before LCM is therefore crucial [71-73]. These processes will not always be necessary as some of these processes may have been carried out by organizations of picture distribution. It is therefore suggested to consult with the distributor of the image and to find out at what stage the image is before purchasing the picture. In many LCM applications, though, pre-processing is regularly not performed further than geometric correction [74]. If distinct RS and ancillary data are used for LCM, there might be differences for obtained pictures or formats, and qualitative assessment of this information is also essential before they can be integrated into a classification method. Just as precise geometric rectification is a pre-processing phase for the combination of distinct source information in the classification method [75]. For large-scale LCM projects, satellite data sometimes have to be used from separate dates. If various scenes are used with expansion of training data from one image to another, normalization of reflection is a needed pre-processing phase [46]. Atmospheric correction is an important component of LCM in different topographical characteristics with remote sensed information [76]. Usually, when multi-temporal or multi-sensory information are applied for LCM, atmospheric calibration is compulsory if a single-date image is utilized in classification, atmospheric correction might not be needed [46]. Another significant component of pre-processing is topographical correction, which affects classification accuracy if the research region is in rough or mountainous areas [77]. Varied terrain alignment always leads to territory pixel signal values to vary. Topographic correction is therefore essential before the LC classification method to quantitatively analyse the RS image.

Number of studies have shown that adjustment of topographical consequences performed prior to the use of multispectral and multi-temporal pixel classification can significantly enhance classification accuracy, especially if the location of the research is in rough terrain [77]. In study [70] realized that the influence of topographic correction techniques on traditional pixel IC has not yet been explored, but many studies that investigate the efficacy of LCM topographic corrections in mountainous terrain are summarized. Multiple writers contrasted the MLC for the most effective topographical correction techniques and recorded an increase in the overall accuracy of 1%-10% [78,79].

In addition, in other studies by [78, 79] and [70] a topographically corrected imagery was implemented to the SVM classifier, achieving appropriate accuracy. The findings indicated that after topographic correction, the precision of the classification of LC improved using Landsat TM-5 and Landsat OLI-8 data, the accuracy rises ranged from 3% to 3.97%, to 0.44% and 1.34%, with Kappa coefficient rises of 2.4% – 4.9% and 1.6% – 2.9%, respectively. In other study, [80] The accuracy of the land cover was evaluated and opposed for the four scenarios. The topographically uncorrected LC classification led in overall accuracies of 78% (1985), 79% (1995) and 84% (2010), respectively. The topographic correction enhanced the classification of MLC classification method with 3% (1985), 3% (1995) and 2% (2010) respectively. The SVM classification method was also carried out on topographically uncorrected and corrected composites. The overall accuracy of the topographically uncorrected SVM classification was 83% (1985), 83% (1995) and 89% (2010), respectively. The revised classification of SVM led in an increase in overall classification accuracies of 2% (1985), 0% (1995) and 2% (2010) respectively. Typically, for all years, the overall accuracies for LC courses were between 78% and 91%.

6.6. Land Cover Features Type and Number

For LCM, different classification techniques had varying benefits in classifying distinct LC features; however, none of researchers could generate ideal classification accuracy for all LC features classifications. [81,82]. One classification method can conduct fairly well in a particular category or feature of LC [83] but there may be some drawbacks to other classifications of LC feature [84]. For example, it was discovered that SVM classification method might have a grassland accuracy of 95%, but only a small housing accuracy of 60.3%. [85]; As well as MLC classification method conducted superior with high accuracy for bare soil (98.01%), but not with much less accuracy for built-up region (75%) [82]. Refer to [83] reported in their tropical forest research, an overall accuracy of 93% was recorded in the forest/non-forest features classification, but that was 86% (producer and user accuracy range 66-95%) when categorized into three groups including non-forest, degraded and logged class.

The number of LC features also effect the LCM process, for example, [80] found a linear relationship type among LCM outcomes accuracies and the number of LC categories or features. This relationship was a significant and weak negative correlation, with $p < 0.05$. Furthermore, the studied concluded that when the number of LC features increase the LCM accuracy also increase. While some research indicates that there is no evident correlation between them, as the p-value is greater than 0.1 base on review done by [86].

6.7. Classification Algorithms and User-Defined Parameters

Distinct classification algorithms produce different results even in the same training data sets and size [87]. Therefore each of classification methods has their own merits for LCM accuracy [46]. Non-parametric classification algorithms have been inferior to standard classifiers in almost all instances like MLC, and MDC. The achievement of non-parametric classifiers can be ascribed to many variables: (1) they cope well with multi-modal, dense and missing information because of their non-parametric nature; (2) they can easily manage both categorical and constant ancillary data; (3) they enable customers to explore the comparative significance of input layers in contributing to classification precision; and (4) they are versatile and can be adjusted for performance improvements for specific issues [88,89]. Often they are recording overall accuracy improvements of 10 to 20 percent than parametric algorithms [90]. While for some application, parametric performs better [91]. Thus give us that understand each classification has it one typical issue.

The performance of any classification algorithms depends on a number of user-defined parameters which may influence the final classification accuracy as discussed in [92]. For example, the following parameters were identified on SVM, as their optimum selection increased the classification accuracy: i) error penalty or cost (C) for all kernels, ii) gamma (γ) for all kernel types except linear, iii) bias term (r) for sigmoid and polynomial kernel, and iv) degree of polynomial (d) polynomial kernel function. However, it is difficult to conclude that any type of kernel for SVM can always outperform all other kernel types on classification because the generalization performance of kernels can vary by different RS data sets and training/testing dataset within IC [93,94].

6.8. Sampling Plan

In LCM, the sampling plan comprises of creating sub-areas from big scenes and generating coordinate pixel records to be used in varying image processing applications, such as IC. The pixel sampling output is commonly a table compiling picture values, and in certain situations these values are marked by place [95]. The choice of a correct sampling plan is essential to evaluate the accuracy of a conceptual model since a bad selection of the sampling plan can create bias in the classification method and the confusion matrix, which may ultimately underestimate or overestimate the real accuracy of the classification [96]. Custer Sampling, Simple Random Sampling, Systematic Sampling, and Stratified Random Sampling are prevalent sampling plans used throughout LCM studies [49]. Three fundamental components have recognized by study [97] to be considered in the design of the plan for an accuracy evaluation plan have been created: the sampling model, the sensitive design and the protocol for evaluation and interpretation. The unit of sampling can be a pixel, fixed area plot or a polygon, however, the optimum unit relies on the application. The study [49] stated that the pixel-based assessment units as bigger units make non-site-specific outcomes. Polygon evaluations often typically lead to progressive classification accuracy reports [98]. Class homogeneity inside the accuracy evaluation unit is attractive, but not essential, and it may influence the map accuracy evaluation if deliberately included. A model-based sample with recognized integration characteristics is ideal, but the ranges among samples should also be sufficiently big to prevent potential spatial auto-correlation impacts. Concepts of accurate and inaccurate answers should be created and quality checks should be carried out prior to use [99].

6.9. Reference Data

Reference data accessibility is a significant factor that affects several elements of an LCM project. A great deal of studies has been carried out on classification techniques, while comparatively few instructions have been released on collection techniques or reference data characteristics for functional LCM projects [100]. In projects in which reference data are sparse or not accessible, information is occasionally gathered for project purposes, often reference data named "purpose-collected." Training samples are sometimes experientially selected sites and homogeneous pixel groups, either recognized on the ground or by other means and often near to highways [101]. Therefore, the operator biases the subjective recognition of training data, but is the most popular technique of building a reference data collection. In administrative initiatives, the availability of reference data, the price of data collection, the traits of the landscape, the satellite data scale, and the objectives of the LCM mission often decide which sort of reference data will be used, and that is another essential role in making the map precise [100].

6.10. Training Samples Data

Training samples are sometimes collect on the ground or from other sources like good maps, aerial photographs and satellite images [102]. The objective of creating training samples is to obtain a set of statistics describing the spectral signal patterns for each LC category to be categorized in the RS data [103]. These samples of practice is used subsequent to train the classification algorithm. Different methods for training collections, such as single pixels, seeds or polygons, can be used, but they might impact the outcomes of data classification process [104]. According to study [101], single pixels and a descriptive sample are proposed as the best selection of training data. Moreover, other study like [104] mentioned single pixels and a descriptive sample are more appropriate for uniform LC earth features. in addition , training samples collected at a single-pixel level and in pixel blocks, revealing that training data array size varied when single-pixel training samples are being used that pixel blocks generated greater accuracy for training in heterogeneous landscapes. Their results, however, may have depended on the specific LC categories for their research.

The scale, number, features of the system and efficiency of training data are also just a few of problems surrounding non-parametric classification training data [105]. For LCM, training samples could comprise of comparatively pure pixels, be recognized from uniform areas in big areas, and be completely exclusive and comprehensive, which can be applied to a variety of classifiers [106]; selection should instead maximize category separability and guarantee that sufficient variability is maintained to make the information member of each category. In the use of training data, there are several temporary elements to acknowledge. Reference data can be gathered from dates other than the satellite image and this can lead to misleading class assignment. The timing of the image creation and the vegetation phenology in regards to the training data must be regarded. In several large-scale projects, satellite images from various dates can be used in mosaics and can include training data upgrade, farther simplifying the use of training data [107]. In addition, when the landscape of a research region is complicated and heterogeneous, it becomes hard to select adequate training samples [46]. The frequency of the classes as shown in in the training data affects the outcomes. In large-scale projects, data on the frequency of classes in the region is beneficial a priori information [108], as entry in the classification supervised.

Supplementary data acquisition and additional training data can be vital steps to improve classification accuracy, particularly in complicated conditions such as mountainous regions. For example [105] founded to integrate ancillary data such as soil types and geographical border pixels of blended spectral features of two crop types in the choice of helpful training samples, significantly reducing training samples prior to classification. They as well looked at the usefulness of introducing additional ancillary data; landform, moisture, and spatial texture to target training samples. Eventually, numerous scientists stress the significance of information on quality assurance and the development of training to achieve accurate classifications (e.g., [104]). Several researchers recommend decreasing the impacts of outliers on training data by weighing samples based on their quality [109], Or through the submission of training data to qualified majority classifiers to detect incorrectly labeled information [110].

6.11. Training Samples Size

Too big a training sample involves resource wastage, and too small a sample reduces the usefulness of the LCM outcomes. Several studies findings revealed a number of formulas and recommendations for selecting a suitable sample size such as [111] recommended a minimum sample of 30 times as many characteristics as possible, it would be appropriate for each class, while [96] proposed at least 50 samples per land-use class. Moreover the study [112] stated a minimum of 10 to 100 times the total of pixels could be used as the results of mean vectors and covariance matrices enhance as the number of training pixels rises (if data is normally spread). Whereas [96] proposed a smallest of 50 samples per LC category. While [99] indicated that a sampling size of 100 samples per class ensures sufficient population assessment. Although [113] mentioned training sample sizes must vary from [30 * Ni * (Ni + 1)] to [60 * Ni * (Ni + 1)] depending on the quality of the issue, where Ni is the number of features or layers input. While he study [109] revealed that a quarter of the initial training samples from SPOT HRV satellite imagery were adequate to generate an extremely high level of accuracy for a two-LC classifier. It is appropriate to take into account not just recognition of spectral variation of a class, as well as the spectral correlation or dissimilarity with other groups [114].Water, for instance, has a spectral signature so different from several kinds of vegetation that it is not really essential to have a precise description of the spectral water variation for accuracy categorization. Taking into account the spectral overlap of class, [115] discovered that sometimes just 2 to 4p training samples were needed per class.

In two studies like [116] (used NN classification method) and [117] (used SVM classification method) found that LCM efficiency mostly depends on a good separation among class boundaries in variable space, thus requiring just minimum and maximum input values for all categories, permitting the size of the training data set. Subsequently, it is also possible to adjust the number of pixels chosen for each class based on the overall significance of the class or the intrinsic variation in each class. Also, it is beneficial to obtain fewer pixels from categories with little to no in-class variation and to boost the number of pixels sampled in categories with an in-class variation. The choice of training samples need to consider the spatial resolution of the RS data and it is often time-consuming because it comprises large regions of mixed pixels, the affordability of ground reference data and the intricacy of study area landscapes. In many instances, it may be hard to have a significant amount of training pixels and therefore, the classifier is not sufficient to incorporate ancillary data [118]. The specifications of the training data set are influenced by the features of the supervised classification technique. Mathematical classifiers that use the mean vector for a class assignment, for instance, are less affected by outliers in training data, whereas classifiers such as NN are extremely affected by individual bad quality training data samples [111]. Whereas, MLC classification method, involve at least p+1 (p = amount of input factors) training samples per class to generate statistics (e.g. matrices of covariance). Based on this, [111] suggested that training samples must be used 10 to 30 times p per class. This limitation is not faced by non-parametric methods, however the total number and intensity of classes in the training data were still influenced.

7. Summary

This paper seeks to navigate via a range of subtopics on Land Cover Mapping (LCM) using Remote Sensing (RS) technology for providing enough information for learners to begin LCM projects. This review paper's structure is as follows; first section gave a review of LCM data type and sources with highlights of the strength and weaknesses of various RS information. Distinct variables are extracted in the second section from RS data. The third section highlights multiple LCM techniques include conventional and remotely sensed methods for accurate LCM with the highpoint of limitations and successes in the application of the RS-based methods. Land cover classification process, steps, and algorithms provided in the fourth section for better understanding of LC classification using RS data and discuss some factors affecting classification process performance.

Multispectral, hyperspectral, light detection and ranging (LiDAR), and radio detection and ranging (radar) as exiting RS data can be used for LCM. From this investigated literature, the choice of appropriate land cover data, however, relies on data accessibility and the particular goal to be obtained. Non-parametric algorithms already tend to be superior to parametric algorithms. However, their efficiency was influenced by numerous variables; landscape, sampling schedule, selection techniques of training, and training size, type of non-parametric algorithms, raw data, etc. Nevertheless, the issue which non-parametric algorithms are better than other LCM algorithms was not normally answered typical with a new lunched satellite (Landsat 8 and Sentinel 2 data). Towards this conclusion, as a suitable non-parametric algorithm with more studies by using new satellites is needed.

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