Journal of Studies in Social Sciences and Humanities
http://www.jssshonline.com/
Volume 8, No. 4, 2022, 387-401
ISSN: 2413-9270

The Utilization of Geospatial Technologies in Urban Vegetation Ecosystems Conservation: A Review

Tolulope Ayodeji Olatoye*
E-mail: olatoyetolu@gmail.com
Department of Geography and Environmental Science,
University of Fort Hare, South Africa

Sonwabo Perez Mazinyo
Department of Geography and Environmental Science,
University of Fort Hare, South Africa

Ahmed Mukalazi Kalumba
Department of Geography and Environmental Science,
University of Fort Hare, South Africa

**Corresponding author*

Abstract
This research is focused on a review of geospatial technologies (such as Remote Sensing and Geographic Information Systems technologies) in monitoring vegetation land use land cover (LULC) conservation. This study is considered very apt and timely because of the ecological challenges and intricacies associated with the paradoxical phenomenon chracterized by conflicting land use practices of urban development as well as the conservation of vegetation LULC in many parts of the world today. It is also imperative to note that the literature reviewed for this research is rich, diversified and developed based on relevant themes in the specific field of study. Relevant literature on the applications of geo-information technologies, and the conservation of vegetation were specifically sourced from internationally recognized academic publications, electronic data sources and other educational websites. This study makes a clarion call towards the conservation of degraded vegetation environments and proffers solutions towards the actualization of environmental sustainability of these fragile ecosystems.

Key words: Change Detection Studies; Ecosystems Conservation; Geography; Geographic Information Systems (GIS); Landuse Landcover Change (LULCC); Remote Sensing (RS); Urbanization; Vegetation.

Introduction

Acording to Olatoye, (2019), land is epitomized as the biological and physical cover on the land surface, including vegetation, water, soil, and other artificial structures. Examples of land cover classes include grassland, deciduous forest and bare soil, water and snow. Change is a natural occurrence on the land and is likely to continue to change in the future. Land cover is therefore important for global monitoring studies, resource management, and planning activities. It is therefore to understand landuse/landcover (LULC) distribution and dynamics, so as to better conceptualize the phenomena, features, productivity and processes of the land, earth's biodiversity, as well as the hydrological and biogeochemical cycles (Ejaro, 2013). According to Giri (2012), the monitoring and assesment of the world's distribution and dynamics of vegetation (such as forests, croplands, grasslands, urbanlands, barren lands, and water resources are essential priorities in environmental studies. Information on LULC change is germane for the conservation, montoring and management of the earth's ecosystem, as well as their changes and consequences.

Justification for the study

It is also imperative to state that this study contributes to science by bringing to the fore the growing complexity of land cover challenges as well as environmental sustainability problems (such as environmental degradation) characterized by coastal urbanization and the intricacies of vegetation conservation.This study underscores the importance that LULC plays as a sink and a source on the global carbon cycle, (Mahmood, 2014), and in the interchange of greenhouse gases between the earth's surface and the atmosphere. However, urban expansion has led to vegetation loss, environmental degradation, higher concentrations of carbon dioxide to the atmosphere, culminating to evapotranspiration, changes in the land-surface albedo, and urban heat island effects , and these are major effects recorded in the study area (Chen, 2015; Orimoloye, 2018). Addditionally, there is very scarce information available on LULLC detection of the entire study area in literature. Hence, this research serves as a viable working document for town planners, ecologists, policy makers and other stakeholders as regards the need for continuous monitoring and conservation of fragile vegetation ecosystems. In light of this, the theoretical framework, the Urban Green Sustainability (UGS) Theory was adopted for this study on account of its support for vegetal resources conservation, which the theory promotes. Further, the research findings helped to harmonize the principles of the UGS Theory with scholarly arguments in literature as well as providing scientific contributions to the actualization of the overarching aim of this study.

Aim of the Study

The aim of this research is to investigate the utilization of geospatial technologies in urban vegetation ecosystems conservation.

Literature Review

Remote Sensing Applications in Urban Vegetation Land Use Land Cover Change (LULCC) Detection

Chen, (2012); Olatoye, (2020) disclosed that urban vegetation LULCC detection denotes the procedure for ascertaining vegetal differences in urban coastal landscapes by investigating them at different periods of time. This procedure can be expedited through manual methods or through automated techniques relating to the utilization of remote sensing (RS) and GIS software. According to Lillesand (2014), the manual methods adopted in the course of deducing urban vegetation LULCC from remotely-sensed satellite imageries or aerial photos requires the analyst or observer to delineate areas of concentration and relating same between imageries from two or more different periods of time. Also, Zou, (2019) stated that in the course of interpreting RS imageries, a stereoscope can be utilized, as this makes provision for two or more spatially-overlaid imageries to be presented in 3D, thereby enhancing the interpretation of RS imageries. The manual methods of interpreting RS imageries is well appreciated when investigating change between distinct and separate vegetation land cover categories (such as coastal vegetation landuses and land cover maps) or when vegetation land cover changes are highly significant such as massive deforestation across territorial boundaries (Zhu, 2016). Additionally, Cabello, (2012) opined that the significance of manual methods of interpreting vegetation land cover changes in RS imageries from different sources cannot be over-emphasized, examples include the comparison of historic RS satelite imageries to present-day ones. On the other hand, there are two types of investigating urban coastal vegetation land cover changes through automated methods namely: Post-classification urban coastal LULC change detection as well as image differentiation with the utilization of band ratios (Hussain, 2013). Post-classification urban vegetation LULCC detection involves the classification or categorization of RS satelite imageries from specific time periods using the same classification pattern into several discrete categorizations, such as urban coastal vegetation land cover types (Blashcke, 2010). Image differenciation on the other hand, involves the technique for generating band ratio such as the Normalized Difference Vegetative Index (NDVI), and the Normalized Difference

Built-Up Index (NDBI) from individual urban vegetation LULC satelite imageries. Consequently, the difference in band ratios is determined between the different periods of time (Thenkabail, 2016).

Schneider, (2012) elucidated the methods adopted in change detection analysis, by evaluating the different algorithms which have been utilized, and these include multi-date composite image change detection (Kavzoglu, 2016), image change algebra detection, image regression, manual on-screen digitization of change (Dewan, 2012) or post-classification comparison detection (Foddy 2012; Chen, 2015).

Issues to Consider in Change Detection Studies

The issues to consider in change detection include image geo-referencing, image resolution and visual inspection, which are discussed in successive sections.

Image Geo-Referencing

According to Comber, (2012); Immitzer, (2016), the art of geo-referencing involves the precise positioning of an image to its actual longitudinal and latitudinal location on the ground. In the eventuality of spatial offsets emanating from the positioning of remote sensors, inadequate Digital Elevation Model (DEM), or relief displacement, the individual pixels denoting specific phenomena on the landscape will not overlap in the imageries being studied, thereby concormitantly leading to erroneous results (Dalponte, 2016). Hence, the extent to which this negatively influences the reliability of the results will be hinged on the magnitude of the geo-referencing errors when investigated in comparison to the phenomena been studied (Eastman, 2013; Houburg, 2015).

Image Resolution

According to Li, (2011), there should be similarity amongst all types of RS satelite image resolution in the individual imageries to be compared. In the same vein, it is advisable to use two images acquired from the same RS satelite, so as to have similar spatial, spectral, and radiometric resolutions accordingly. With reference to temporal resolution; it is appropriate that the two scenes of remotely-sensed data to be compared are derived from similar sunlight angular inclinations and time periods, as this will concormitantly reduce errors associated with incident light, shadows, as well as the amount of foliage (El-Kawy, 2011; Giri, 2012).

Visual Inspection

It is discovered in literature, (such as Campbell, 2011) that the change detection begins with the visual comparison of co-registered RS satelite images from two different periods of time, even if the main research motive is to utilize automated algorithm techniques for LULC change detection and/or classification. It is on this consideration that most GIS/RS image processing software incoporate tools to carry out overlay functions, indepth/detailed observation, as well as side-by-side viewing of imageries (Blaschke, 2014). In some cases, manual digitizing methods may be adopted in the course of identifying and classifying LULC changes, as well as in speeding up the most appropriate automated LULC change detection technique to be utilized for any related study (Atkinson, 2012).

Pre-Classification Change Detection

According to Avelar, (2014), pre-classification LULC change detection incorporates the art of simply subtracting the pixel value in one image from the pixel value of the second image from the same geographical location. This technique is performed within the GIS software environment, and it is both conceptually and computationally simple and fast (Mbolambi, 2016). RS satelite imageries incorporates several individual co-registered bands of colours (Dewan, 2012). According to Guo, (2019), it is expedient to state that multispectral digital camera has four (4) bands, and these include: near-IR, green, blue and red; while Landsat 7 comprises of seven (7) bands (Reece, 2019). Additionally, the process of band differencing can only be adopted to one band per time, and it is a herculean task to distinguish or tell apart different LULC features on the composite image based on the "color" that is seen (Guha, 2018). In addition, each of the spectral bands contain atmospheric effects, hence, it is imperative to corrected atmospheric errors from one RS image to another (Steffen, 2010).

Post-Classification (Thematic) Land Cover Change Detection

According to Vittek, (2014) and Zou, (2019), post-classification LULCC detection involves the procedure for generating two independent thematic rasters with the aid of the supervised method of image classification. Thereafter, the change detection procedure is then applied by comparing the before classes and after classes in each pixel. With higher input classes, the results become easier to interpret visually, and GIS tools can be utilized in quick simplification of results for presentation to policy makers and decision makers. As put forward by Kpienbaareh, (2018), it is important to state that thematic, or post-classification, change detection results are characteristically of low accuracy on account that the accuracy of results is hinged on the correctness of the input classification data. In the course of analyzing change detection in vegetation studies, certain classification approaches must be adopted (Rawat, 2015).

Several scholars (such as Hansen, 2013; Kavzoglu, 2016; Kpienbaareh, 2018; Olatoye, 2020) have opined that image classification utilizes spectral data on contained within image spectral bands by categorizing pixels into various classes. According to Li, (2018), the most commonly utilized applications of supervised classification procedures include the maximum likelihood (MLC), and minimum distance classifiers, and the duo are utilized with multispectral and hyperspectral data sets correspondingly. MLC utilizes randomly selected training data to compute the probability of a specified pixel by approximating the mean and variance and then assigning the pixel to the envisaged class that seems most likely appropriate (Pu, 2012). Further, the MLC procedure computes or calculates the probability on the premise that the data are evenly distributed. Hence, urban coastal vegetation land cover mapping using RS images yield more valid and reliable results through the utilization of supervised classification technique in classifying pixels of known and unknown identity through unsupervised methods of classification (Cabello, 2012; Klemas, 2013). In addition, supervised classification employs manual means in identifying the training areas that are a representation of the desired classification categories/classes (Selvam, 2012). Furthermore, it is imperative to randomly select suitable training areas and hitherto instruct the classifier to detect and distinguish the different land cover classes (Zhu, 2016). Classification methods utilized in vegetative LULC mapping include pixel and object-based classifications, and vegetation indices.

Pixel-Based Classification (PBC)

According to Liu (2010), PBC is a conventional process of classification based on categorizing individual pixels with the adoption of supervised and unsupervised classification procedures. However, it is expedient to state (as postulated by Rapinel, 2014; Zou, 2019), that traditional PBCs based on spectral dissimilarities are an inappropriate approach for differentiating vegetation land cover types with similar spectral resolution characteristics.

Object-Based Classification (OBC)

According to Fensholt, (2012); Kavzoglu, (2016), OBC is a traditional method which involves the categorization of spectrally-homogenous pixels through the process of Image Segmentation (IS) and thereafter grouping the individual LULC phenomena being studied (Liu, 2010; Campbell, 2011). The operationalization of the OBC technique is possible sequel to the derived information from an array of similar pixels/ objects in the RS imagery. On the other hand, IS permits the use of additional attributes or features such as the texture, shape, size, colour of the land cover image when analysing the image attributes. According to Kavzoglu, (2016), the performance of the OBC procedure is determined by the quality and accuracy of the image segments. The OBC approach has merits over the PBC approach in 2 ways. First, minimization of salt-and-pepper effects as well as the reduction in "within-class" spectral variation is a characteristic feature when changing the classification units from pixel format to image objects in the PBC approach (Weih, 2010). Second, a large array of attributes distinguishing the object's spatial, textural and contextual characteristics greatly enhances the direct spectral observations of the

RS imagery, and this concomitantly advances the accuracy and veracity of results derived from classification. Several studies have adopted the OBC technique in various investigations involving vegetation monitoring as well as in terrestrial and coastal LULC change detection studies (Lück-Vogel, 2013; Cho, 2015). In a study conducted by Lück-Vogel, (2013), his research involved the adoption of the OBC approach in the evaluation of natural vegetation health and intactness, using segmented multispectral RS satellite imagery. From the foregoing, the OBC procedure utilized derived information regarding the structural (compactness), textural (NIR standard deviation) as well as spectral (brightness) of the LULC attributes of the study area, and the procedure yielded reliable results, with 80% as the overall accuracy, using Landsat TM imageries and 90 to 95% accuracy for the SPOT 5 imageries. Hence, it is on this premise that Lück-Vogel, (2013) made a clarion call in favour of the OBC technique in LULC studies, which could be enhanced by the respective LULC attributes. It is also germane to note that both techniques have their peculiar limitations, for instance, the limitations associated with OBC technique include errors that occur in the course of carrying out segmentation process, and these errors can either be due to under-segmentation or over-segmentation (Hussain, 2013). On the other hand, the errors associated with the PBC technique occur during the "within-class" spectral variation, the salt-and -pepper effect, as well as errors emanating from mixed pixels (Liu, 2010). Other methods used in vegetation LULC classification include the hybrid procedure, and as the name implies, it involves the integration of both the OBC and PBC procedures, and this procedure was adopted in mapping the coastal vegetation LULC of the French Atlantic coastline (Rapinel, 2014).

Normalized Difference Vegetation Index (NDVI)

According to Singh, (2016) and Kpienbaareh, (2018), Normalized Difference Vegetation Index (NDVI) is a classification technique, which has been widely operationalized in several ecological studies, for assessing, gauging, quantifying as well as computing biomass and vegetative energy through the integration of two or more spectral bands (Campbell 2011). Studies such as that of Petach, (2014) have evaluated the quantity of reflected sunlight intensity from the earth and photosynthetic capacity of vegetation land cover. Consequently, the interpretation of findings according to Van, (2015), states that the vegetal cover in a pixel is if there are higher levels of radiation, which is reflected in near infrared (NIR) wavelength, than those recorded in the visible wavelengths. On the other hand, there will be sparse vegetal LULC (such as grassland, tundra or desert) if the rate of radiation in the NIR is slightly more than that of the reflected visible wavelength. According to Holme, (2014), this is a reliable assertion, because the high chlorophyll content, which characterizes robust/dense vegetation, absorbs light that is more visible and this consequently results in greater reflectance of NIR energy, while a reverse scenario occurs in sparse vegetation, which reflects lesser quantities of NIR, which depicts unhealthy mesophyllic leaf structure, and poor vegetal LULC. Rouse et al. in the Texas University Centre initially adopted NDVI as a procedure in vegetation biomass mapping in 1973 for Remote Sensing. Pettorelli, (2014) elucidates the importance of NDVI in ecological and vegetation conservation mapping. It serves as a dependable correlative index in the assessment of vegetal energy as well as the functionality of varied ecological systems (Reif, 2017). As opined by Mbolambi, (2016), NDVI values vary from -1.0 to 1.0, and this means that values less than zero typify the absence of vegetal cover, while figures that are beyond 0.5 depict dense/robust vegetal LULC (Wang, 2010; Sinha, 2015).

Landsat Thematic Imageries

According to Vittek, (2014); Zhu, (2016), Landsat satellites collect data on phenomena on the earth's surface, as they are known to revolve in the polar orbit and their functionlity is programmed with the rotation of the earth (Sarkhosh, 2012). Landsat has special capabilities in LULC monitoring, change detection, urbanization, climate change, carbon sequestration, wildfire, drought and a host of other studies centred on natural or anthropogenic causes.The satelite collects data by using passive sensors onboard the satellite that detect radiation emitted from the earth in different bands. Landsat satellite orbits at 705 kilometers (about 438 miles above the earth), at 98.2^0 inclination, circumnavigates the earth every 99 minutes, with a 16-day temporal resolution, crossing the equator at 15 minutes earlier or later than 9.45am (Seong, 2015). The Landsat Thematic Mapper (TM) is characterized by a spatial resolution of 30 meters, and comprising of six (6) spectral bands, with Band 6 as a thermal band. Landsat satellites have special capabilities in LULC monitoring, change detection, urbanization, climate change, carbon sequestration, wildfire, drought and a host of other studies centred on natural or anthropogenic causes. Landsat satellites are passive sensors because they do not produce their own radiation, but obtain insulation from the sun as well as thermal radiation from the surface of the earth. Table 1 depicts an annotated bibliography of LULCC studies.

Several scholars have conducted studies on LULC change detection. An annotated bibliography on LULC change studies is depicted in Table 1.

Table 1:

Annotated Bibliography on LULC Change Studies

S/N	Author	Research Topic	Interval of change detection studied	Results from land cover change detection
1.	Deng, (2010)	Spatio-Temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization	1996-2006 (10 years)	The results indicated that the rapid urbanization process has brought about enormous land use changes (composing of altogether 79.83% of the total change) and urban growth at an unprecedented scale and rate and, consequently, given rise to substantial impacts on the landscape pattern.
2.	Zhao, (2010)	The use of thematic mapper data for change detection and sustainable land use of cultivated land: Case of Yellow River Delta, Cnacan	1987-1998 (11 years)	The study utilized multi-temporal composite and classification, and image rationing when remote sensing data acquired in the suitable season are available, and distinct spectral characteristics of different land use types exist. The results showed that the area of cultivated land in this region decreased by 5321.8 ha over the period 1987 to 1998, 483.8 ha every year, mainly concentrated in the central paddy field region and northeast dry land region.
3.	Mendoza-González (2012)	LULCC and its effects on the value of ecosystem services; Case of Gulf of Mexico	1995-2006 (11 years)	The results indicated that from 1995–2006, urban sprawl was a major phenomenon. There was a net loss ($US 2006/ha/year) of $\$1.4 \times 10^3$ in Boca del Río, $\$7 \times 10^5$ in Chachalacas and $\$1 \times 10^5$ in Costa Esmeralda. Yet, after losing ecosystem resources, the seeming gains from urbanization are lost.
4.	Beuchle, (2015)	Landcover changes in the Brazillian Cerrado and the Caatinga biomes based on remote sensing approach	1990-2010 (10 years)	The quantity of natural vegetal cover left in the Cerrado was less than 50% and less than 65% in the Caatinga respectively, with the yearly net rate of vegetation loss in the Cerrado reduced from $-0.79\%\ yr^{-1}$ to $-0.44\%\ yr^{-1}$ from the

				1990s to the 2000s, while in the Caatinga for the same periods the rate increased from −0.19% yr^{-1} to −0.44% yr^{-1}. In summary, these Brazilian biomes witnessed both losses and gains of vegetal cover; although a continuos vegetal net loss was detected in the two biomes to urbanization in the period under review.
5.	Rawat, (2015)	Monitoring land use and land cover changes using remote sensing and GIS techniques. A case of Hawalbagh block, Uttarakhand, India.	1990-2010 (20 years)	Satelite imageries of Hawalbagh block, Uttarakhand were characterised into 5 classes: vegetation, waterbodies, agriculture, bare land and built-up areas. The results specified that vegetation and built-up land have been increased by 3.51% (9.39 km^2) over the last 20 years, and 3.55% (9.48 km^2) while agriculture, barren land and water body have reduced by 1.52% (4.06 km^2), 5.46% (14.59 km^2) and 0.08% (0.22 km^2), correspondingly. The study demonstrates the importance of LULCC detection applications in the study area.
6.	Butt, (2015)	LULCC mapping using remote sensing and GIS. A case of Simly watershed, Islamabad, Pakistan	1992-2012 (20 years)	LULCC detection was expedited with the utilization of SPOT 5 and Landsat 5 satelite imageries fortand were utilized from 1992-2012. The in the study area was categorized into 5 main LULC classes: Vegetation, Cropland, Rocks/Bare soil, waterbodies and settlements. The resultant LULC and overlay maps that were generated in ArcGIS 10 environment depicted a major alteration from vegetation to cropland, and bare soil/rock and settlements reduced by 38.2% and 74.3% correspondingly. These LULC changes greatly threatened the watershed resources.
7.	Jana, (2016)	Seasonal change monitoring and mapping of coastal vegetation types along Midnapur-Balasore coast, Bengal, using multi-temporal landsat data	2000-2015 (15 years)	The results depicted that from year 2000-2002, there was a high depletion of coastal vegetation by 61.83 ha, due to high human activities, commercial aquaculture, which greatly eroded the LULC of the study area. The NDVI derived from ETM+ images were useful in monitoring the coastal LULC changes, particularly the mangroves, salt marsh vegetations as well as the natural vegetation growing on sand dunes.
8.	Zhu, (2016)	Including land cover changes in analysis of greeness trends using all available Landsat 5.7 and 8 images: A	2000-2014 (14 years)	The study assessed the consistency of surface reflectance from Landsat 5, 7 and 8. In the analysis of greenness trends for Guangzhou. In spite of massive amounts of development in Guangzhou from 2000 to 2014, greenness

		case study from Guangzhou, China		increased, mostly because of gradual change. Overall, this analysis demonstrates the importance of considering land cover change when analyzing trends in greenness from satellite time series in areas where land cover change is common.
9.	Kalumba, (2018)	Assessing industrial development influence on land use/cover drivers and change detection in West Bank, East London, South Africa	1998-2013 (15 years)	The study revealed that 22.4% of the vegetation in the study area was converted into built-up, 32.7% of water areas were colonised by vegetation, and close to half (42.12% and 41.6%) of the bare land and built-up changed to vegetation respectively. For the period, 2007 – 2013, less than a quarter (10.1%) of the vegetation was transformed into built-up, while more than one-third (33.6%) of the built-up, 14.3% of water and more than half the bare land were converted into vegetation. The rest of the changes were very minimal and varied across classes.
10.	Olatoye, (2020)	Geospatial analysis of LULCC detection of coastal vegetation loss at Bufallo City Metropolitan Municipality (BCMM), South Africa from 1998-2018		This study is an excerpt of the author's doctoral research titled "Effects of urban expansion on the coastal vegetation ecosystems conservation and functioning at Bufallo City Metropolitan Municipality (BCMM), Province of the Eastern Cape, South Africa". For this study, the statistical calculation of re-coded LULCC, NDVI and NDBI images derived from Landsat 5 of 1998 and 2008, as well as Landsat 8 OLI TM imageries of BCMM of 2018 were carried out in ArcGIS 10.8 environment. The MLC results revealed that the aerial coverage of grassland vegetation increased from 605.205 km^2 to 1735.9 km^2 from 1998 to 2018 respectively, amounting to about 41% increase. Also, forest cover had diminished in aerial extent from 804.9km^2 in 1998 to 338km^2, which is approximately 17% loss. Also, LULC classification results were validated by performing the Normalized Difference Built-Up Index (NDBI), Normalized Difference Vegetative Index (NDVI) and the results also revealed that the built-up area had increased from 194 km^2 in 1998 to 814 km^2 in 2008.

Table 1 depicts the anotated bibliography of LULCC studies of some scholars. LULCC are two distinct expressions frequently used interchangeably in the course of this study. Further, LULC information and their optimum utilization is indispensable for the selection, development and execution of land use structures to cater for increasing demands by the locales (Acheampong, 2015). LULC records also fosters land use dynamism emanating from changing demands of population expansion. In spite of the fact that LULC changes do not necessarily denote land degradation, nevertheless, natural and anthropogenic factors, which are motivated by an array of social origins (Stefanidis, 2013). Consequently LULC changes lead to distress biodiversity and other processes that ultimately culminate in biospheric and climatic challenges (Zaehle, 2014).

According to Vittek, (2014); and Olatoye, (2020), landsat satelites are very useful for vegetation LULC mapping and change detection studies. From the foregoing, Table 2 depicts the characteristics of landsat satelites.

Table 2:

Characteristics of Landsat Satelites

Name of satelite	Location above the earth	Spatial resolution	Spectral resolution	Temporal Resolution	Special Capabilities of Landsat
LANDSAT	705 km	30 metres	6 to 9 bands	16 days	Special capabilities in LULC monitoring, change detection, urbanization, climate change, carbon sequestration, wildfire, drought and a host of other studies centred on natural or anthropogenic causes.

Table 2 reveals that Landsat satellite orbits at 705 kilometers (about 438 miles above the earth), at 98.2^0 inclination, circumnavigates the earth every 99 minutes, with a 16-day temporal resolution, crossing the equator at 15 minutes earlier or later than 9.45am (Seong, 2015). The Landsat Thematic Mapper (TM) comprises of 6 spectral bands with 30 meter-spatial resolution, and Band 6 as a thermal band. Landsat satellites have special capabilities in LULC monitoring, change detection, urbanization, climate change, carbon sequestration, wildfire, drought and a host of other studies centred on natural or anthropogenic causes. According to Potatov, (2012), Landsat satellites are passive sensors because they do not produce their own radiation, but obtain insulation from the sun as well as thermal radiation from the surface of the earth.

Maximum Likelihood Classification (MLC)

Image Pre-processing of BCMM Satelite Imageries

According to Schowengerdt, (2012), image pre-processing is a procedure carried out on satelite imageries, with the purpose of determining the lowest level of abstraction. Pre-processing helps to ehance the data quality of sateite imageries data so as to suppress distortions, and thereby enhance the essential features of the imageries which are necessary further processing. Image pre-processing is carried out in land cover studies to adjust image values so as to analyze or depict information within the image and to enhance capabilities for the visual deduction of spatial phenomena characterizing an imagery. This procedure endeavours to boost the complementary capabilities of the human conceptualization and computers (Clerici, 2014). In vegetation LULC studies, predominantly multi-temporal images of 30-m Landsat Thematic can be utilized (Zhu, 2016; Olatoye, 2020), however, for more recent years, Landsat 8 OLI satellite imagery can be employed. A systematic archiving of remotely-sensed data gathering can be obtained from the USGS website (Jana, 2018). The reason for choosing the above-named source is because is free and accessible online. Also, the path and row of the Landsat image to be studied must be identified through the Worldwide Reference System (WRS).

"Path" is defined as the descending orbit of the satellite, while "Row" refers to the latitudinal centre line of a frame of imagery (Seong, 2015). Consequently, the steps to be followed in LULCC assessment includes image pre-processing, feature extraction, selection of suitable classification approaches and training samples, post-classification processes and accuracy assessment. As suggetsted by Guha, (2018), it is expedient to carry out radiometric and geometric correction on the satelite images in order to enhance their quality From the foregoing, the satelite imageries should be auto-rectified and projected to the local coordinate system by using the WRS. Also, all the selected images are required to be of good quality of less than 10% cloud cover, hence, atmospheric and radiometric corrections should be performed in a GIS software environment for visual inspection (Deng, 2010; Rawat, 2015; Olatoye, 2020). Thereafter, all the bands making up the multi-temporal imageries were then combined in the GIS software. Three-band combinationss of the multi-spectral images are performed to produce the false colour images of LULC features such as forest forest vegetation, grassland, urban, water and bare ground. The use of bands combinations in LULCC analysis enhances the spectral separation of the image, and this further improves the interpretability of data (Kavzoglu, 2016; Olatoye, 2020). The activity flow chart adopted for LULCC studies is presented in Figure 1.

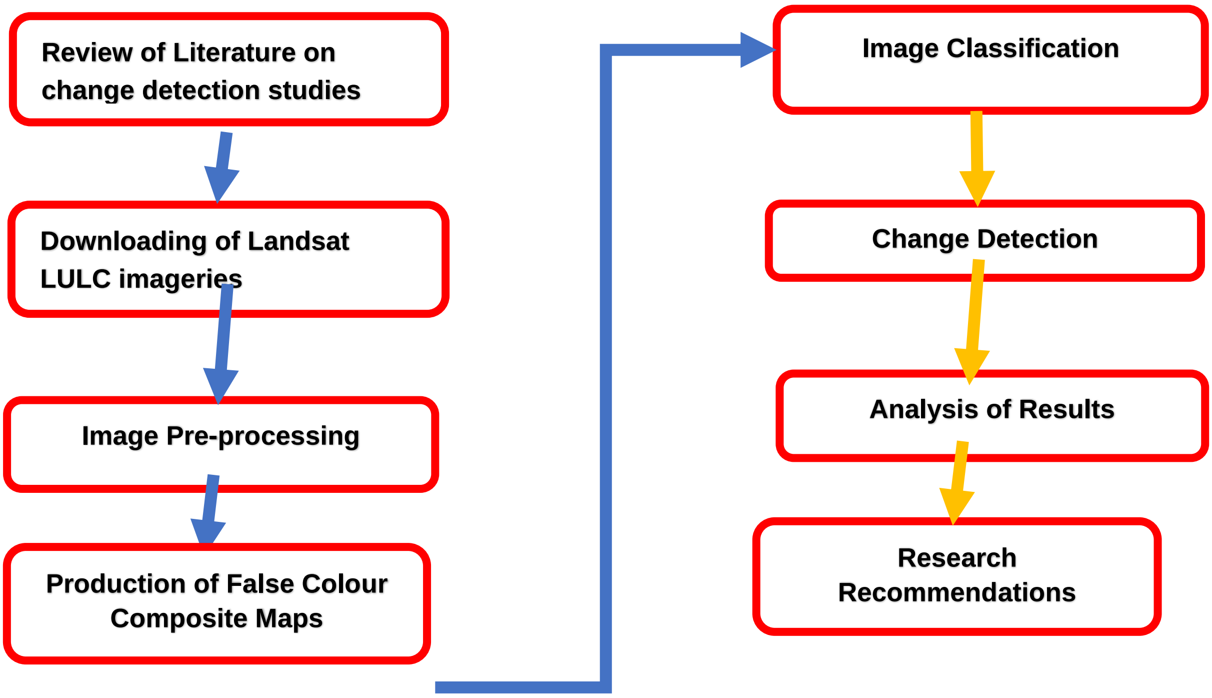

Figure 1: *Activity Flow-Chart for Vegetation LULCC Detection*

Image Pre-Processing Procedure

According to Olatoye, (2020), the shapefile for the vegetation LULC area should be drawn and used to clip the needed area from the entire region. Thereafter, the art of mosaicking should be performed for the imageries during the study years under review. The art of mosaicking involves the process of combining or merging two or more images so as to create a single raster dataset from multiple raster datasets, and was thereafter extracted through the feature extraction procedure, while keeping as much information as possible from large data sets of the image. In order to enhance the interpretability of the vegetation LULC imageries, false colour composite images are produced through supervised and unsupervised LULC classification. They are created by assigning red, grey, and blue colours to each of the individual monochrome bands of the multispectral imageries and then superimposing them (Kavzoglu, 2016). The light and dark red colours represent the forest and grassland vegetation respectively, while grey and blue colours depict built-up areas and water bodies respectively. In urbanized settings, FCC imageries exemplify the multispectral image generated using colour combinations that can distinguish many different functions. Vegetation appears in red color on account of the chosen combination of bands and the reflection of near- infrared light (Steffen, 2010; Vivone, 2014; Thenkabail, 2016), and the deeper the shade of red, the more robust the vegetation, and this is due to greater reflectance of higher chlorophyll levels in the EMS (Wang, 2015). It is also essential to note that these enhanced/developed images only serve visual analyzing purposes, while the original images are utilized in the automated analysis, hence, the researcher employed contrast stretching technique on the three selected images for visual analysis, thereafter, the images are conventionally classified into five (5) classes namely: Bare ground, water bodies, forest vegetation, grassland and urban areas (Vittek, 2014; Olatoye, 2020). The identification of these five categories are recognized on account of the visual analysis of the RS data and substantiated from ground-truthing exercises which were expedited during field work. Thus, the description of land cover classification is further described in Table 3.

Description of Land Cover Classes

According to Deng, (2010); Varshney, (2013); Rawat, (2015); Thenkabail, (2016); Olatoye, (2020), vegetation LULC can be classified through MLC into five (5) classes namely: Bare ground, water bodies, grassland, forest vegetation, and built-up areas, and these are further explained in Table 3 below.

TABLE 3:
Description of Land Cover Classes

S/N	Classes	Description of Land Cover Classes
1.	Bare Ground	Areas of bare rock, sand, silt, gravel or other earthen material with little or no vegetation including beaches and sandy areas. Other examples include areas of bedrock, desert pavement, scarps, talus slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits, and other accumulations of earthen material.
2.	Water Bodies	Areas of open water, generally with less than 25% cover of vegetation or soil. All types of water such as sea and lakes.
3.	Forest Vegetation	Areas dominated by trees generally greater than 5 meters tall, and greater than 10% of total cover. More than 75% of tree species maintain their leaves all year. Canopy is never without green foliage. They are commonly found around steep slopes and less populated areas. Canopy cover of 50–80%. Total canopy cover around 90%, typically a mix of trees (60%), shrubs (20%), grasses (10%) and unproductive land (10%).

4.	Grassland	Land cover dominated by shrubs and crops that are less than 5 meters in height. These areas are also subject to intensive management such as tilling, and can be utilized for grazing. These areas also account for more than 70% of the land, and are frequently observed on level lands (plains, plateaus, foot slopes and valley floors).
5.	Built-Up Areas	Areas characterised by a density of human structures such as houses, commercial buildings, asphalt, concrete, and artificial surfaces. They include areas of residences, administrative buildings, industrial and trade enterprises.

The selection of training samples for each of the predetermined categories of LULC types is expedited by delineating polygons around each category of LULC classes. Thereafter, the spectral signatures for the corresponding LULC categories is depicted by the remotely-sensed images which are derived from the pixels within the polygons. According to Al-doski, (2013) and Vivone, (2014), a spectral signature assesses success levels in LULC mapping, and hitherto minimizes misclassifications that may arise during LULC analysis. The major change detection procedure steps carried out in vegetation LULCC studies is presented in Figure 2.

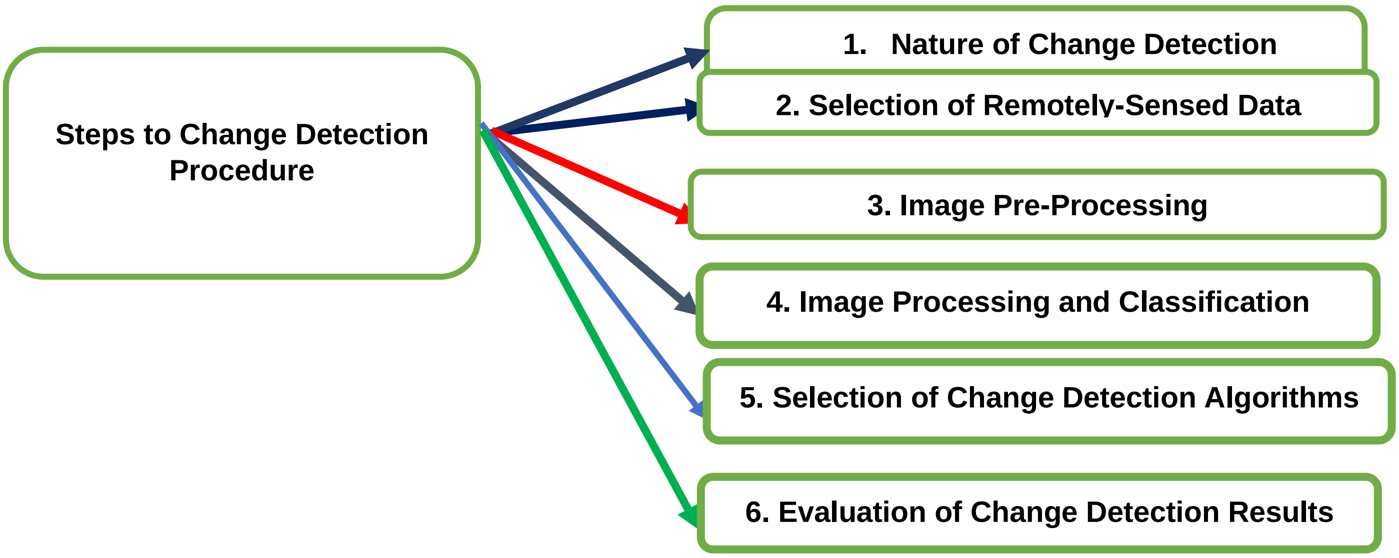

Figure 2: *Major Change Detection Procedure Steps Carried Out in Vegetation LULCC Studies*

Conclusion

Information about the spatio-temporal analyisis of vegetation LULC studies is indispensable for biodiversity conservation, ecology, as well as urban planning studies, and also provides scientific guidance when addressing urbanization problems. It has been emprically observed that human activities hve gretly altered LULC on the earth surface within the last 150 years and has culminated in the discharge of enormous carbon into the atmosphere. LULCC has had more negative than positive consequences on the environment. Further, LULCC detection enhances in analyzing the impact of urban expansion on vegetation LULC , which has led to degraded ecosystems, drastic decline of biodiversity, exacerbated environmental degradation, and subsequently aggravating risks of endangering fragile ecosystems all over the world.

Implications for Research

This article underscores the importance of geospatial technologies, such as remote sensing and Geographic Information Systems in monitoring, evaluation, assessing, planning as well as projecting for urban vegetation resources in order to ensure its optmal growth, conservation and its sustainable use for medicinal purposes, furniture making, etc while ensuring that the urban vegetation ecosystems are protected and conserved while serving as habitat to fauna resources. Further, this study contributes to research through the enhancement of knowledge on ecological systems by promoting measures geared towards ensuring the functionality of all components of urban ecosystems, such as vegetation, air, water and wildlife. In the same vein, the study makes a clarion call towards promoting ecological conservation through the regulation of water, soil, biodiversity, carbon fixing, surrounding wildlife habitat, in addition to offering several ecological benefits in urban areas. Further, this study significantly contributes to scientific knowledge with regards to ecosystem services in changing landscapes, synergistic interactions of provisioning, regulating, as well as cultural ecosystem service provisioning at local and regional levels. Additionally, the assessment of responses on ecosystems services and changes to the landscape changes and the development of place-based theories on ecosystems services are actualized.

ACKNOWLEDGEMENT

The authors acknowledge funding for this research, which was provided by Govan Mbeki Research and Development (GMRDC), University of Fort Hare, Alice, south Africa.

References

Acheampong, K. O. (2015). Tourism policies and the space economy of the Eastern Cape Province of South Africa: A critical realist perspective. *African Journal for Physical Health Education, Recreation and Dance*, *21*(3.1), 744-754.

Avelar, S., & Tokarczyk, P. (2014). Analysis of land use and land cover change in a coastal area of Rio de Janeiro using high-resolution remotely sensed data. *Journal of Applied Remote Sensing*, *8*(1), 083631.

Beuchle, R., Grecchi, R. C., Shimabukuro, Y. E., Seliger, R., Eva, H. D., Sano, E., & Achard, F. (2015). Land cover changes in the Brazilian Cerrado and Caatinga biomes from 1990 to 2010 based on a systematic remote sensing sampling approach. *Applied Geography*, *58*, 116-127.

Butt, A., Shabbir, R., Ahmad, S. S., & Aziz, N. (2015). Land use change mapping and analysis using Remote Sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan. *The Egyptian Journal of Remote Sensing and Space Science*, *18*(2), 251-259.

Cui, L., & Shi, J. (2012). Urbanization and its environmental effects in Shanghai, China. *Urban Climate*, *2*, *1-15*.

David, A., Guilbert, N., Hamaguchi, N., Higashi, Y., Hino, H., Leibbrandt, M., & Shifa, M. (2018). Spatial poverty and inequality in South Africa: A municipality level analysis.

Deng, J. S., Wang, K., Hong, Y., & Qi, J. G. (2010). Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization. *Landscape and urban planning*, *92*(3-4), 187-198.

Goble, B. J., Lewis, M., Hill, T. R., & Phillips, M. R. (2014). Coastal management in South Africa: Historical perspectives and setting the stage of a new era. *Ocean & coastal management, 91, 32-40.*

Gomera, S., Chinyamurindi, W. T., & Mishi, S. (2018). Relationship between strategic planning and financial performance: The case of small, micro-and medium-scale businesses in the Buffalo City Metropolitan. *South African Journal of Economic and Management Sciences, 21(1), 1-9.*

Jana, A., Maiti, S., & Biswas, A. (2016). Seasonal change monitoring and mapping of coastal vegetation types along Midnapur-Balasore Coast, Bay of Bengal using multi-temporal Landsat data. *Earth Systems and Environment*, 2(1), 7.

Kalumba, A.M., Olwoch J.M. Aardt, I. Van, Adeola A.M, Malahlelaa O. Nsubuga F.W.N. (2018): Assessing Industrial Development Influence on Land use/Cover Drivers and Change Detection for West Bank East London, South Africa. *International Journal of Applied Engineering Research.*

Karanam, H. K., & BabuNeela, V. (2017). Study of normalized difference built-up (NDBI) index in automatically mapping urban areas from Landsat TM imagery. *International Journal of Engineering, Science and*, *6*, 239-248.

Klemas, V., 2013. Remote sensing of coastal wetland biomass: an overview. *Journal of Coastal Research: Volume 29, Issue 5: pp. 1016 – 1028.*

Kpienbaareh, D., Kansanga, M., & Luginaah, I. (2018). Examining the potential of open source remote sensing for building effective decision support systems for precision agriculture in resource-poor settings. *GeoJournal*, 1-17.

Li, K., & Chen, Y. (2018). A Genetic Algorithm-based urban cluster automatic threshold method by combining VIIRS DNB, NDVI, and NDBI to monitor urbanization. *Remote Sensing*, *10*(2), 277.

Lillesand, T., Kiefer, R. W., & Chipman, J. (2014). Remote sensing and image interpretation. *John Wiley & Sons.*

Mbolambi C. (2016): Assessment of coastal vegetation degradation using remote sensing in False Bay, South Africa. Thesis submitted in fulfilment of MSc in *Geography & Environmental Studies, Stellenbosch University*.

McCarthy, Matthew J., Merton Elizabeth J., and Muller-Karger, Frank E. (2015): Improved coastal wetland mapping using very-high 2-meter spatial resolution imagery. *International Journal of Applied Earth Observation and Geo-information* 40 (2015) 11–18

Mendoza-González, G., Martínez, M. L., Lithgow, D., Pérez-Maqueo, O., & Simonin, P. (2012). Land use change and its effects on the value of ecosystem services along the coast of the Gulf of Mexico. *Ecological Economics*, *82*, 23-32.

Mohamed, M. A. (2017). Monitoring of temporal and spatial changes of land use and land cover in metropolitan regions through remote sensing and GIS. *Natural Resources*, *8*(05), 353.

Olatoye, T.A. (2020). Effects of Urban Expansion on Coastal Vegetation Ecosystems Conservation and Functioning in Buffalo City Metropolitan Municipality, South Africa: *Doctoral thesis, Department of Geography and Environmental Sciences, Faculty of Science and Agriculture, University of Fort Hare, Alice, South Africa: January, 2020. 329pp.*

Olatoye, T.A.; Kalumba, A.M; Mazinyo, S.P; and Odeyemi, A.S. (2019): Ecosystem Functioning, Goods, Services and Economic Benefits in Buffalo City Metropolitan Municipality (BCMM) Eastern Cape, South Africa. *Journal of Human Ecology. REF. NO. JHE-038-19*

Olatoye, T.A.; Mazinyo, SP; and Odeyemi, AS (2021). Forest systems services provisioning in Africa: Case of Gambari Forest Reserve, Ibadan, Nigeria: *International Journal of Forestry*

*Research***, Hindawi Limited,** London W1T 5HF, United Kingdom. *V*ol. 2021, Article ID 8823826. Available Online at: https://www.hindawi.com/journals/ijfr/2021/8823826.

Probeck, M., Ramminger, G., Herrmann, D., Gomez, S., & Häusler, T. (2014). European forest monitoring approaches. In *Land Use and Land Cover Mapping in Europe* (pp. 89-114*). Springer*, Dordrecht.

Rapinel, S., Clément, B., Magnanon, S., Sellin, V., & Hubert-Moy, L. (2014). Identification and mapping of natural vegetation on a coastal site using a Worldview-2 satellite image. *Journal of environmental management*, 144, 236-246.

Rawat, J. S., & Kumar, M. (2015). Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Science*, 18(1), 77-84.

Sarkhosh, A. (2012*). Remote Sensing and GIS models-based approach to the Land Cover Classification on Ahipara region using RapidEye and Landsat 7 (ETM+)* (Doctoral dissertation, Auckland University of Technology).

Sharma, A. (2015). *Mapping of agro-forestry and horticulture plantations in Bist Doab Track of Punjab using remote sensing and GIS* (Doctoral dissertation, Punjab Agricultural University, Ludhiana).

Sinuka, S. S. (2017). *The Socio-Environmental Impacts of Sewage Spills on Communities in East London, Eastern Cape, South Africa* (Doctoral Thesis, University Of Fort Hare).

Taubenböck, H., Wiesner, M., Felbier, A., Marconcini, M., Esch, T., & Dech, S. (2014). New dimensions of urban landscapes: The spatio-temporal evolution from a polynuclei area to a mega-region based on remote sensing data. *Applied Geography*, *47*, 137-153.

Tavares, P. A., Beltrão, N. E. S., Guimarães, U. S., & Teodoro, A. C. (2019). Integration of Sentinel-1 and Sentinel-2 for Classification and LULC Mapping in the Urban Area of Belém, Eastern Brazilian Amazon. *Sensors*, *19*(5), 1140.

Thenkabail, P. S., & Lyon, J. G. (2016). Hyperspectral remote sensing of vegetation. *CRC press.*

Turok, I. (2012). Urbanization and development in South Africa: Economic imperatives, spatial distortions and strategic responses. London: Human Settlements Group, International Institute for Environment and Development.

Varshney, A. (2013). Improved NDBI differencing algorithm for built-up regions change detection from remote-sensing data: an automated approach. *Remote sensing letters*, *4*(5), 504-512.

Vittek, M., Brink, A., Donnay, F., Simonetti, D., & Desclée, B. (2014). Land cover change monitoring using Landsat MSS/TM satellite image data over West Africa between 1975 and 1990. *Remote Sensing*, *6*(1), 658-676.

Zhao, G. X.; Lin G. & Warner T. (2010): Using Thematic Mapper data for change detection and sustainable use of cultivated land: a case study in the Yellow River delta, China. *International Journal of Remote Sensing*. ISSN: 0143-1161

Zhu, Z., Fu, Y., Woodcock, C. E., Olofsson, P., Vogelmann, J. E., Holden, C., ... & Yu, Y. (2016). Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014).