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Land cover land use mapping and change detection analysis using geographic information system and remote sensing

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ABSTRACT

Land cover/land use categories are relevant components in land management. Understanding how land cover/land use change over time is necessary to assess the consequences of humans and natural stressors on the earth's environment and resources. The aim of the study was to map and monitor the spatial and temporal change in land cover/land use for the periods of 1977, 1991 and 2016 and to predict change detection areas in Davidson County, Tennessee. The land cover/land use categories were classified using maximum likelihood algorithm and post classification comparison change detection analysis was performed. Classified image differencing technique was also used to predict change detection areas in Geographic Information System. The land cover/land use categories were successfully classified with a kappa value of about 78%. The land cover/land use classes changed significantly from 1977 to 2016 in Davidson County, Tennessee. Wetlands and bare land had a net decrease on average of about 97% between 1977 and 2016 whereas; developed areas and forest had a net increase on average of around 40% between 1977 and 2016. Urbanization appeared to be one of the main drivers of the change in land cover/land use. This information could be used in land management and planning by environmental managers, policy makers and other stakeholders.

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INTRODUCTION

Globally, land cover/land use are changing continually due to natural and human factors such as seasonal changes, cities expansion, forest regeneration and degradation and transformation of land dedicated for forestry to farmland. Land cover refers to the physical characteristics of the earth's surface, captured in the distribution of vegetation, soil, water and other physical features of the earth whereas; land use is the way in which land has been used by humans and their habitat, usually with an emphasis on the functional role of land for economic activities (Liping *et al.*, 2018; McConnell, 2015). However, land cover/land use are often used interchangeably (Liping *et al.*, 2018; Rawat and Kumar, 2015). Understanding land cover/ land use will help provide quantitative projection of future land cover change. Furthermore, it provides a pathway to comprehend the impacts of diverse land management options in addition to feedbacks to the environment to

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better manage land resources. The Davidson County which constitutes the city of Nashville (largest city in the state of Tennessee) has experienced dramatic population increase in recent years (Mojica, 2018). The population of Davidson county increased from about 477,800 in 1980 to around 678,889 in 2015 (United States Census Bureau, 2018). The increase in population is driving important environmental change in the region including economic development. Although economic developmental activities such as residential and urban expansion are important to humans' existence, land cover/land use change can generate significant negative impacts to ecosystems sustainability and biodiversity in which humans depend for their livelihood. A change in water resources can influence drought conditions and thereby affects water quantity and quality. Therefore, there is a need to spatially and explicitly quantify change in land cover/land use to support planning or decision making processes. Satellite remote sensing provides a data source to generate multi-temporal images of the earths' surface and change detection techniques helps to understand landscape dynamics. Satellite images with spectral information can be classified to identify regions and attributes on the environment to generate multi-temporal maps. With multi-temporal environmental maps, it is easier to detect and quantify temporal and spatial difference in a given area. Recent study in the United States utilized Landsat satellite information for the years 2001, 2006 and 2011 to identify change in land cover/land use (Homer *et al.,* 2015). They found net gain and loss in land cover classes across the conterminous U.S. coastal zones with some land cover categories changing more than once during a 10-year period. For example, open water reduced in geographic extent by about 2,268km^2 between 2001 and 2006 and increased in extent by about 3,941 km^2 between 2006 and 2011. This trend was similarly found in cultivated crops which decreased by about 2,312 km^2 between 2001 and 2006 and increased in extent by around 696 km^2 between 2006 and 2011. Developed areas increased within the 10 years' period of study whereas; forested areas decreased within the same period with significant change in land cover categories east of the United States compared to west (Homer *et al.,* 2015). Although the study captured important change in land cover/ land use, it examined environmental change within in a small window of 10 years period. As a result, it did not adequately capture the long term land cover/ land use change especially within Davidson County, Tennessee that has had a long-term gradual increase in population. This study presents a new dataset showing historical change in land cover/land use categories within Davidson County, Tennessee-USA for the periods of 1977, 1991 and 2016 using Landsat satellite data. It aims to map and monitor the spatial and temporal change in land cover/land use classes within these periods and to predict change detection areas. For example, what change in land cover/ land use classes occurred within Davidson County, Tennessee? How much change occurred among these categories? Where did change occur and where did change not occur within the area of study? This information will be useful to urban planners and land managers for land use planning and management purposes. This study has been carried out in Nashville Tennessee in 2018.

MATERIALS AND METHODS

Area of Study

The region ranges from latitude 35°58'15'' to 36°22'49'' N and longitude 86°36'45''to 86°54'43'' W. (Fig. 1).

The region is made up of the city Nashville and surrounding suburbs with population of about 678,889 in 2015 (United States Census Bureau, 2018). It is the second largest county in Tennessee by population (United States Census Bureau, 2018) and among the counties in the United States of America with rapid growth (Sellers, 2018). The study area was selected because of the rapid growth in population over the decades (Mojica, 2018, Sellers, 2018). The rapid growth in urban population has likely caused significant change to the environment due to increased pressure on ecosystem services and resources.

Climate

Davidson County experience modest climatic conditions with cool winters and warm summers (Hodges *et al.,* 2018). It has mean annual temperature closed to 78°F (26°C) in summer and approximately 41°F (5°C) in winter. Yearly precipitation is generally about 51 inches (1,300 mm) and are usually distributed uniformly throughout the seasons (Hodges *et al.,* 2018). May generally has the highest

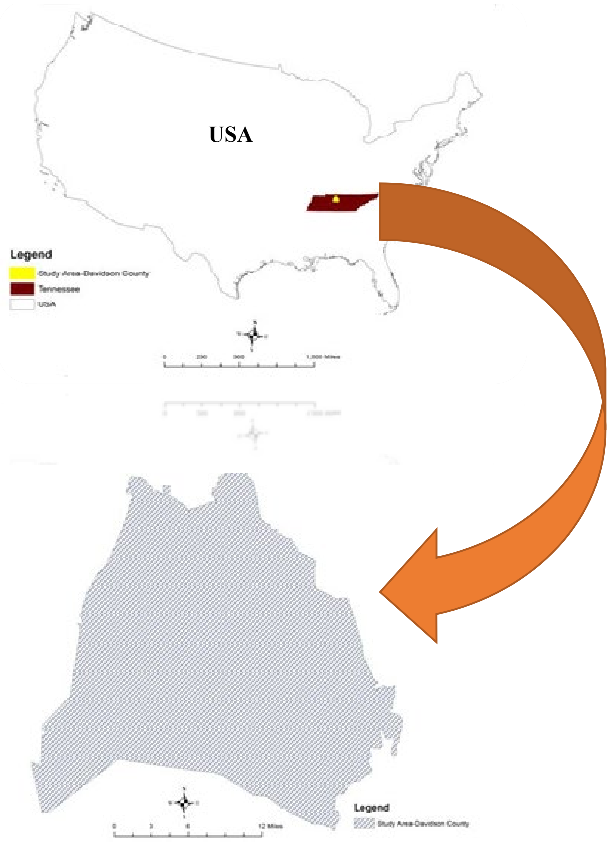

Fig. 1: Geographic location of the Area of Study-Davidson County, Tennessee

monthly average precipitation of about 5.51 inches whereas; October has the lowest monthly average rainfall of around 3.03 inches (United States Climate Data, 2018). The month of June has an average rainfall of around 4.13 inches and the month of September has an average rainfall of about 3.43 inches (Unite States Climate Data, 2018).

Geology and hydrology

Davidson county is made up of a combination of gentle and highland terrains (Hodges *et al.,* 2018). The surrounding central basin generally has alkaline soils whereas, the highlands usually have acidic soils (Mitsch *et al.,* 2009). The gentle terrain and highlands are intermittently cut across by major rivers including the Cumberland River which flows southwards (Mitsch *et al.,* 2009). Reservoirs have been created around the Cumberland River to manage flooding during high rainfall periods. Many streams have been re-directed for cultivation and agricultural purposes (Meador, 1996).

MATERIAL AND METHODS

The methodological approach mainly includes land cover/land use classification and mapping within Davidson County, Tennessee using Landsat 2, Landsat 5 and Landsat 8 satellite images (Fig. 2). An assessment of the temporal and spatial change in the land cover categories was also performed using post classification comparison technique. In addition to examining the change in land cover/land use, the study predicted areas where land cover/land use change occurred and areas where change did not occur within the selected dates of satellite data acquisition. The classification and delineation of land cover/land use categories involved remotely sensed digital image acquisition, pre-processing, classification and validation phases (Fig. 2). Land cover/land use maps generated were then exported as raster files to Geographic Information System environment (GIS) for change detection analyses.

Areas predicted where transformation in land cover/land use occurred and areas where no transformation occurred was also performed in the GIS environment.

Land cover/Land use classification, mapping and change detection

Landsat 2, 5 and 8 satellite images attained in the months of May 1977, September 1991 and June 2016 respectively were processed for land cover/land use distribution within Davidson County. One satellite scene representing each of the data acquisition date covering Davidson County was downloaded from the United States Geological Society (USGS) Science Data repository. The images were selected because they had zero percent of cloud cover and were within the thirty-nine years of change detection study window. The satellite images were acquired as Level-1 images and required atmospheric and radiometric calibrations. Three remote sensing image processing phases' i.e. preprocessing, classification and accuracy assessment/validation phases (Fig. 2) were used to generate and map land cover/land use classes from the three Landsat scenes representing the three data acquisition dates.

The Landsat 2, 5 and 8 satellite images were cropped to the study area, georeferenced, co-registered and calibrated radiometrically in the preprocessing stage. The geometric calibration was carried out using greater than 50 ground control points and a root mean square (RMS) value of lower than 1 pixel. The radiometric calibration involved the transformation of digital numbers (DN) to spectral reflectance. The radiometric calibration entails the correction of image pixel values for sun elevation angle variation and image calibration to account for sensors degradation over time. The changes in sensors calibration factors will obscure real changes on the ground (Mather, 1999). Landsat 8 scene

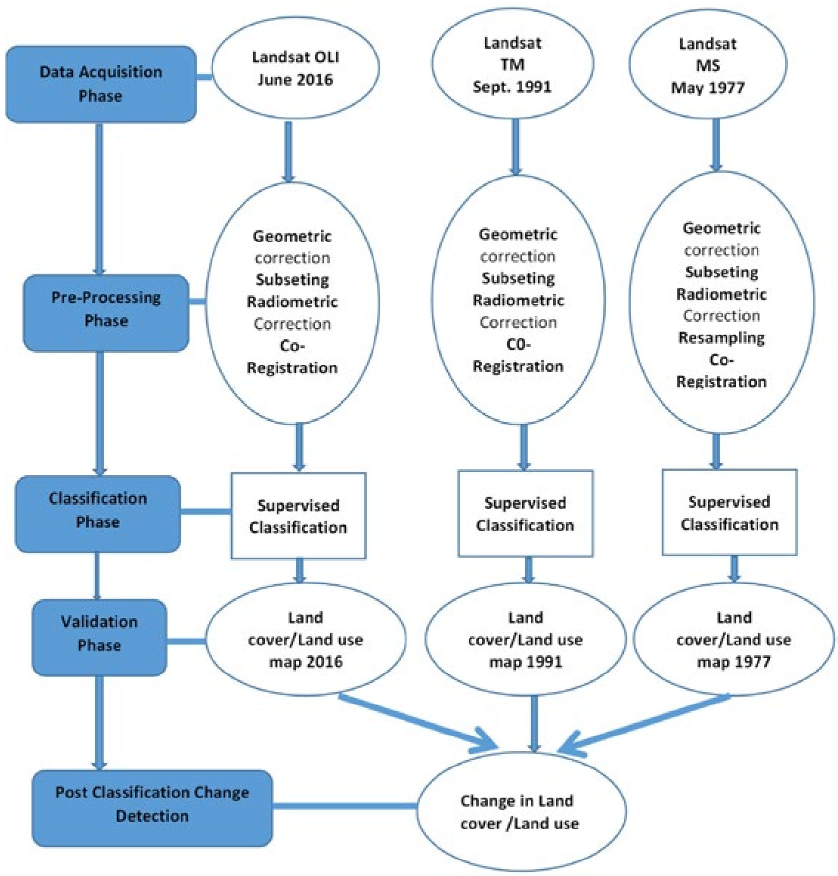

Fig. 2: A graphical display of the methodology used in the study

was converted from digital numbers to spectral reflectance through Eq. 1 (National Aeronautics and Space Administration, 2018).

$$\rho\lambda' = M_p Q_{cal} + A_p \quad (1)$$

In which:
$\rho\lambda'$ = Spectral reflectance lacking solar angle correction
M_p = Multiplicative rescaling factor for individual bands
A_p = Additive rescaling factor for individual bands
Q_{cal} = digital numbers

The multiplicative and additive rescaling factors for Individual bands were derived from the header files.

In addition, spectral reflectance with solar angle correction was generated through Eq. 2 (National Aeronautics and Space Administration, 2018).

$$\rho\lambda = \rho\lambda'/\sin(\vartheta_{SE}) \quad (2)$$

In which:
ρλ = Spectral reflectance with correction of solar angle
ρλ' = Spectral reflectance lacking solar angle correction
ϑ_{SE} = sun elevation angle in degrees

Landsat 2 and 5 scenes were converted from digital numbers to radiance through Eq. 3 (Akumu *et al.,* 2010, National Aeronautics and Space Administration, 2017).

$$L_{rad} = \text{Bias} + (\text{Gain} \times \text{DN}) \quad (3)$$

In which:
L_{rad} = Spectral radiance, $W/m^2/sr/\mu m$
DN = Digital number.

The spectral values of gain and bias for Landsat 2 and 5 data were obtained from the image header files.

The transformation of spectral radiance to spectral reflectance for Landsat 2 and 5 was obtained through Equation 4 (Akumu *et al*., 2010, National Aeronautics and Space Administration, 2017).

$$RTOA = (\pi \times L_{rad} \times d^2)/ (ESUN_i \times \cos (z)) \quad (4)$$

In which:
RTOA= Spectral reflectance
L_{rad} = spectral radiance
π = ≈ 3.14159
$ESUN_i$ = the mean solar exoatmospheric irradiance for the individual bands
d = the earth-sun distance, in astronomical units, which is calculated using the following EXCEL equation (Archard and D'Souza, 1994, Eva and Lambin, 1998).

d = (1 − 0.01672 × *COS* (*RADIANS* (0.9856 × (*Julian_Day* − 4)))).

z = solar zenith angle (zenith angle = 90 − solar elevation angle), solar elevation angle is derived from the header files.

The land cover/land use classes were classified based on the land cover/land use categories described in Anderson *et al*. (1976). They were visually detected in Google Earth Pro version 7.3.2.5491 and polygons were digitized around the various categories in Google Earth Pro environment. The polygons were exported as Keyhole Markup Language (KML) files and converted to shape files in GIS environment. The land cover/land use polygons constituted the training information used to classify and map the various types of land cover/land use in the entire region of study. The study used visible and infrared spectral bands in the classification and mapping process. In the processing phase, the training information polygons were utilized in the extraction of spectral signatures of land cover/land use through supervised maximum likelihood classification algorithm. This is because maximum likelihood classification uses both the mean vectors and variance information of training data to create probability statistics of a given pixel to belong to a particular class. The land cover/land use categories generated for 2016 satellite imagery were validated to examine how well the classified map represented the various land cover on the ground. The validation/accuracy assessment phase was carried out by selecting about 197 polygons from the classified map and comparing them to Google Earth Pro information representing land cover on the ground. Site visitations were also carried out to compare polygons on the map to field information on the ground. The study generated the overall accuracy of the classification by dividing the sum of the correct diagonal values in the error matrix table with the sum of all pixels in the error matrix table (Congalton, 1991). The kappa value was also derived through the method described by Mather (1999). Due to lack of past data on land cover/land use for Davidson County, the study did not carry out validation on the classified maps generated for the years 1991 and 1977. The digitally classified land cover/land use maps were converted from raster to vector in GIS for further analyses. Spatial extent and temporal change detection analyses were performed in ArcGIS environment. Post classification comparing change detection approach was performed between the generated land cover/land use categories. Prediction of change detection areas was carried out through image differencing technique in ArcGIS. The image difference tool in spatial analyst GIS extension was used to predict areas where change occurred and areas where no change occurred between the dates of satellite data acquisition. The image difference tool assigns the land cover/land use category values to the most recent image where change occurred and assigns a value of zero to the image on areas where change did not occur (Environmental Systems Research Institute, 2018).

RESULTS AND DISCUSSION

Land cover/ land use classification and mapping

The land cover/land use categories included agriculture, bare land, developed areas, forest, grassland, shrub land, water and wetlands (Fig.3-5). The land cover/land use categories were distributed across Davidson County in the years 1977, 1991 and 2016. Developed areas were concentrated in the central parts of the county with open water (i.e. the Cumberland River) flowing and cutting across the county. Similarly, bare land occurred mostly in the middle parts of the region especially in 1977. Agricultural areas were found mostly around major rivers and streams because farmers prefer close access to water for irrigation purposes. Forest and shrub land occurred throughout the region but were predominantly in the western parts relative to the eastern portions of the study area in the years of 1977, 1991 and 2016 (Fig.3-5). The occurrence of wetlands in the region was very isolated and limited in distribution especially for the year of 2016. The construction and development of more wetlands in the region will be beneficial because they provide habitats to a variety of species and regulate hydrological processes (Cohen *et al.,* 2016).

The study classified and mapped land cover/land use categories with about 81% overall accuracy in the 2016 classification (Tables 1 and 2). The producer accuracy which is the ability of the classification algorithm to generate land cover/land use categories was highest (100%) for water and lowest (68%) for shrub land. In contrast, the user accuracy which demonstrates how well the classified land cover/ land use categories on map actually represent land cover/land use on the ground was maximum (96%) for water and developed areas and minimum (65%) for wetlands. The kappa value (78%) which indicates the correlation between the classified land cover/ land use categories to the reference data (Google

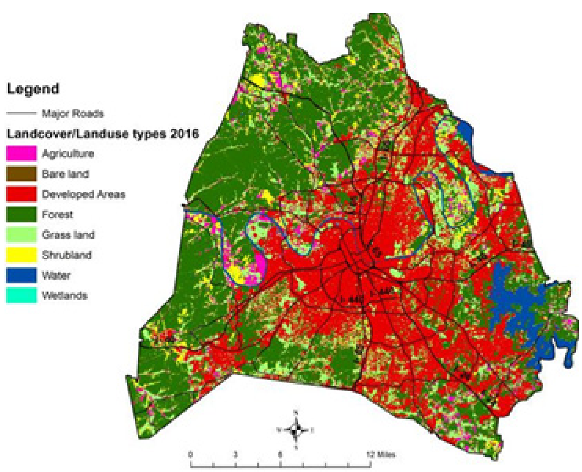

Fig. 3: Derived land cover/ land use classes and distribution within Davidson County (June 2016)

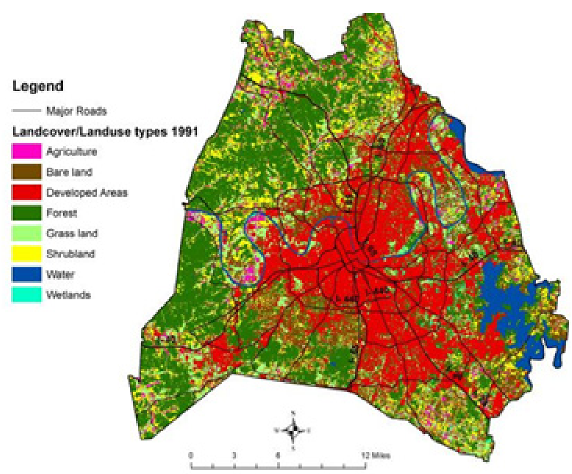

Fig. 4: Derived land cover/land use classes and distribution within Davidson County (September 1991)

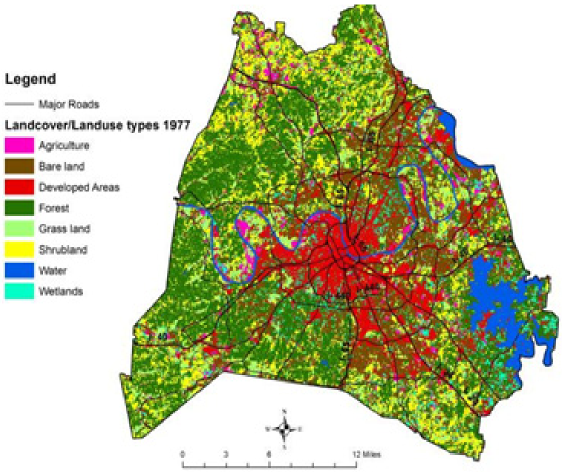

Fig. 5: Derived land cover/land use classes and distribution within Davidson County (May 1977)

Earth or Field data) showed a very good to excellent correlation. This is because kappa values of 75% and above are considered very good to excellent correlation and kappa values below 40% are considered poor correlation assuming the data are randomly sampled from a multinomial distribution with a large sample size (Montserud and Leamans, 1992).

The percent cover of land cover/land use categories varied among years in which the satellite data were acquired (Fig. 6). In 1977, forest had the highest percent cover (24%) while agriculture and water bodies had the lowest percent cover of about 4% each (Fig. 6). Developed areas had the most percent cover (25%) in 1991 whereas; wetlands had the least percent cover of about 3% in 1991. The high percent cover of developed areas further confirms

Table 1: Generated Error Matrix Table for Land cover/Land use classification of 2016

Land cover/ land use classes	Wetlands	Grass land	Bare land	Water	Shrub land	Agriculture	Developed	Forest	Total
Wetlands	15	2	0	0	2	1	0	3	23
Grassland	0	25	0	0	0	5	0	0	30
Bare land	0	1	12	0	0	0	2	0	15
Water	1	0	0	25	0	0	0	0	26
Shrub land	0	2	0	0	15	1	0	4	22
Agriculture	2	3	0	0	0	20	0	0	25
Developed	0	0	1	0	0	0	25	0	26
Forest	3	0	0	0	5	0	0	22	30
Total	21	33	13	25	22	27	27	29	197

Table 2: Generated Accuracies from Error Matrix Table for Land cover/Land use classification

Land cover/Land use Types	Producer Accuracy (%)	User Accuracy	Overall Accuracy	Kappa Statistics
Wetlands	71	65		
Grassland	76	83		
Bare land	92	80		
Water	100	96		
Shrub land	68	68		
Agriculture	74	80		
Developed	93	96		
Forest	76	73		
Overall and Kappa value			81	78

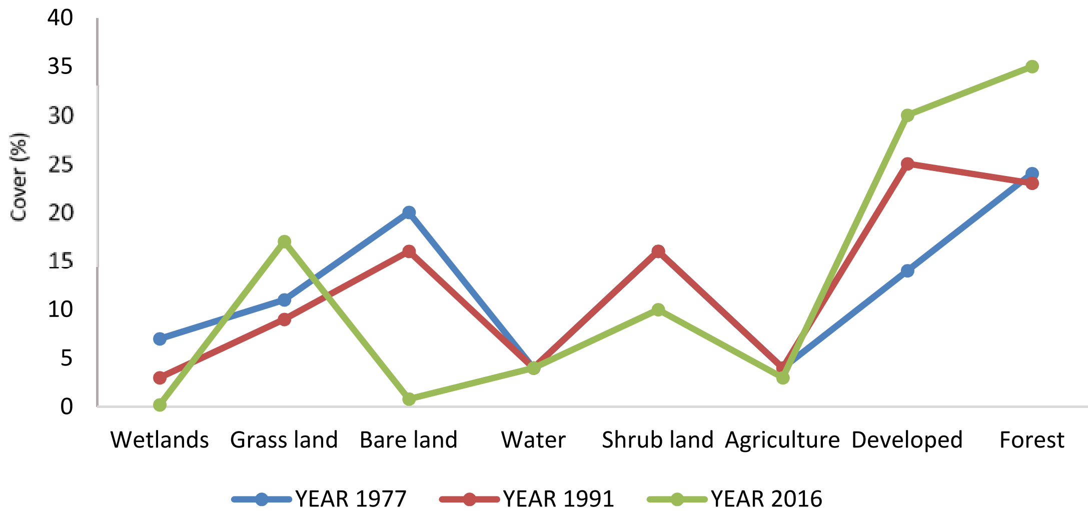

Fig. 6: Percent cover of land cover/ land use categories in Davidson County for the years 1977, 1991 and 2016

Table 3: Change in the extent of land cover/ land use classes in Davidson County, Tennessee

Land cover/ land use classes	May 1977 - Landsat MSS 2	September 1991-Landsat TM 5	June 2016-Landsat OLI 8	% Change May1977 & Sept 1991	% Change May1977 & June 2016	% Change Sept.1991 & June 2016
	Area (ha)	Area (ha)	Area (ha)			
Wetlands	9620	4243	316	-56	-97	-92
Grassland	14400	12613	22107	-12	35	43
Bare land	27290	22171	997	-19	-97	-96
Water	5886	5309	4644	-10	-21	-13
Shrub land	22231	20822	13490	-6	-39	-35
Agriculture	5262	5259	3512	-0.06	-33	-33
Developed	18261	34053	39505	46	54	14
Forest	33069	31549	45033	-4.6	27	30

the rapid increase in human activities that has occurred in Davidson County since the 1970s (United States Census Bureau, 1996). This will likely have significant environmental impact such as increased pollution on the surrounding water resources (Luo *et al*., 2018, Wang and Kalin, 2018, Xia *et al*., 2017). The developed areas represented built-up areas such as residential, factories, administrative buildings, airports, roads and bridges. In 2016, forest had the maximum percent coverage (35%) among the land cover/land use categories whereas; wetlands had the minimum percent coverage in the area of study (Fig. 6). There is still a significant amount of forest land still available in the area of study and the region is playing a critical role in carbon sequestration and storage. Although forest occupied most of the region in 2016, the forest coverage might reduce in the future because of the rapid increase in population in the region. Enhancing urban afforestation policies within the county could help minimize the threat of population boom on forest cover.

Analysis of land cover/land use change

The study found significant change in land cover/land use categories within Davidson County, Tennessee between 1977, 1991 and 2016 (Table 3). Wetlands decreased by about 56% between 1977 and 1991 and decreased by about 92% between 1991 and 2016 (Table 3). The decline in wetlands between 1977 and 2016 is likely as a result of wetland drainage due to urban development. The decrease trend in wetlands is also similar to bare land which decreased by about 19% between 1977 and 1991 and about 96% between 1991 and 2016. In the years 1977 and 2016, both wetlands and bare land decreased by about 97 % on average. Residential development is the most likely driving factor contributing to the decrease of wetlands and bare land in Davidson County, Tennessee. Shrub land also decreased by about 6% between 1977 and 1991 and decreased by about 35% between 1991 and 2016. The loss of shrub land from 1977 to 2016 is likely due to the conversion of shrub land to forest cover. The subtropical climate contributes significantly to the rapid growth and conversion of shrub land to forest. However, with future change in climate, significant shift in tree species composition is expected in the region (McCarthy *et al.,* 2018, Pacheco *et al.,* 2010). Likewise, in Agriculture, a significant decrease of about 33% was found between 1991 and 2016. The net loss in agricultural land between 1991 and 2016 is likely due to transformation of agricultural land. Agricultural area was converted to other land cover/land use types predominantly developed areas. Urbanization provides a significant threat to croplands and this will inherently threaten global food security, increase sustainability risks and threaten the livelihood of citizens (d'Amour *et al.*, 2017, Schwaab *et al.,* 2017). The study found developed areas increased by about 46% from 1977 to 1991 and around 14% from 1991 to 2016. On average between 1977 and 2016, developed areas had a net increase of about 54%. The change in developed areas is as a result of urbanization and residential development to accommodate the increase in population in the region. The increasing trend in developed areas is consistent with the findings of Homer *et al* (2015) where they found a net gain in developed areas across the conterminous U.S. coastal zones for the periods of 2001 and 2011. In contrast, forest and grassland decreased by about 4.6% and 12% respectively between 1977 and 1991. Furthermore, forest and grassland increased by around 30% and 43% respectively between 1991 and 2016. On average, both forest and grassland increased in extent by about 20% from the periods of 1977 to 2016 in the region. The primary driver for the increase in grassland is likely urbanization. This is because newly constructed residential buildings are usually designed with grassland lawns for aesthetic and recreational purposes. Furthermore, the primary driver for the increase in forest land in the region is primarily due to afforestation and conversion of shrub land to forest. Open water bodies decreased by about 10% in the years 1977 and 1991 and around 13% in the years 1991 and 2016. This is probably due to seasonal change in weather conditions and patterns in the region such as precipitation and temperature. The large extent in water bodies in May of 1977 relative to September 1991 and June 2016 is likely due to the high amount of precipitation usually experience in the region in month of May relative to other months of the year (United States Climate Data, 2018).

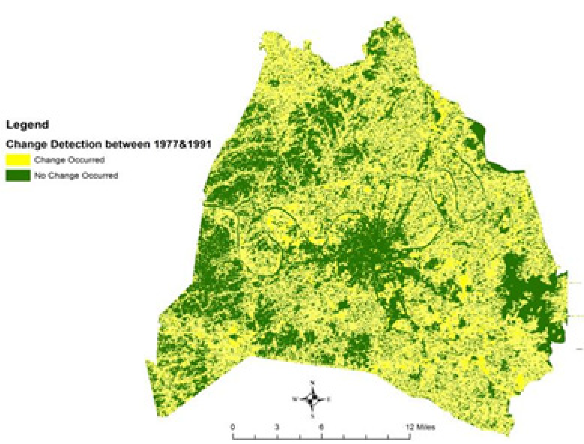

Fig. 7: Change detection areas between 1977 and 1991

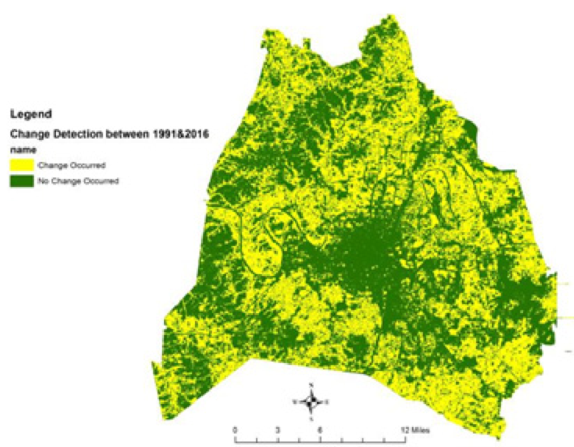

Fig. 8: Change detection areas between 1991 and 2016

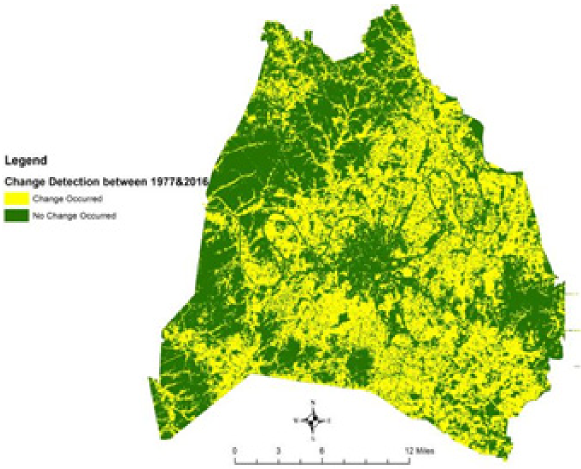

Fig. 9: Change detection areas between 1977 and 2016

In the years of 1977 and 1991, the change in land cover/land use occurred in about 64% of the study area whereas; no change occurred in about 26% of the region (Fig. 7). The change occurred throughout the area of study especially in the north, south and eastern portions of the region. No change occurred mostly in the central and western portions of the region. Most of the change occurred with net wetlands loss and net developed areas gain. In contrast, the least of the change occurred with net agriculture and forest loss in the years of 1977 and 1991.

Land cover/land use change occurred between 1991 and 2016 in about 54% of the region whereas, no change occurred in around 46% of the region (Fig. 8). All land cover/land use categories experienced some degree of change during the time periods of 1991 and 2016. Bare land experienced most change with a net bare land loss while water bodies experienced the least change with a net water loss. No change also occurred mostly in the central and western portions of the region within the time periods of 1991 and 2016.

In the years of 1977 and 2016, land cover/land use change was detected in about 49% of Davidson County whereas, no change was detected in around 51% of the study area (Fig. 9). Similarly, to the other years, the change occurred mostly east of the region compared to the west. This implies more developmental activities have occurred east of Davidson County compared to the west. Examining the impacts of the land cover/land use change on the environment within Davidson County is an area for further research.

Understanding the distribution and transformation of land cover/ land use is vital for land use planning and management in the region. Furthermore, these digital maps could be useful in other applications such as vulnerability and impact assessments modeling (Akumu *et al.,* 2018).

CONCLUSION

The land cover/land use categories in Davidson County, Tennessee have been successfully classified and mapped using Landsat satellite data for the years 1977, 1991 and 2016. The study found a very good correlation between the classified land cover/land use classes and reference data with kappa value of about 78%. Forest and developed areas occupied most of Davidson County in the time periods of satellite data attainment. The study found significant change in land cover/land use classes in 1977, 1991 and 2016. Wetlands and bare land had an average net loss of about 97% between 1977 and 2016 whereas; grassland and developed areas had an average net gain of about 45% between 1977 and 2016. The land cover/land use change predominantly occurred east of the county relative to west. No change in land cover/land use occurred predominantly in the middle sections and west of the county. Urbanization, afforestation, conversion of shrub land to forest and agricultural conversions appeared to be the primary land cover/land use change drivers in Davidson County, Tennessee. This information improves our understanding of where land cover/land use change occurred in the region. Furthermore, it quantitatively assessed what land cover/land use changed over time between 1977, 1991 and 2016. This new dataset is important for land management and planning purposes and could be useful in future prediction of land cover/land use change.

CONFLICT OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

ABBREVIATIONS

°C	Degree Celsius
Cos	Cosine
°F	Degree Fahrenheit
GIS	Geographic information system
ha	Hectare
i.e.	That is
km^2	Square Kilometer
m	Meter
mm	Millimeter
MSS	Multi Spectral Scanner
N	North
OLI	Operational Land Imager
TM	Thematic Mapper
US	United States
W	West
$W/m^2/sr$	watt per square meter per steradian
^{0}	Degree
µm	Micrometer
()	Bracket
%	Percent
/	Or

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