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Impervious Surface Mapping Using Remote Sensing linear spectral mixture analysis

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Abstract

Impervious surface has been recognized as a key indicator in assessing urban environments. However, accurate impervious surface mapping is still a challenge. Effectiveness of impervious surface in urban land-use classification has not been well addressed. This work explored mapping of impervious surface information from Landsat images. A new approach for urban land-use classification, based on the use of impervious surface, was developed. The advancement of remote sensing technology has made it easy in assessing urban growth. In this study, the utility of Linear Spectral Mixture Analysis (LSMA) which is a sub-pixel classification method was used in the analysis of Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus imagery to map urban physical components in Mubi town. The three physical components of urban Land Cover (LC): impervious surface, vegetation and soil, were used in the LSMA. LSMA decomposes each pixel to address the heterogeneity of urban LC characteristic by allowing the number and types of end members to vary on a per pixel basis. This study generated spectral mixture models of 2-, 3-, and 4-endmembers for each pixel to estimate the fractions of impervious surface, vegetation and soil in the study area with a constraint of lowest root mean square error (RMSE). An analysis of the impervious surface areas (ISA) mapped with LSMA demonstrated that it produced more accurate results of mapping urban physical components. CVA maps the impervious surface areas and proves the increase of such areas from 1987 to 2012 as well the decrease of them from 1987 to 2012 in vegetation. Human activities such as over-grazing, over-cultivation and tree cutting contribute highly to the impervious surface in the study area. With the multiyear Landsat TM data, we quantified sub-pixel %ISA and the %ISA changes to assess urban growth in the Mubi town, during the past twenty five years. The experimental results demonstrate that the LSMA approach is effective in mapping and monitoring urban land use/land cover changes using moderate-resolution multispectral imagery at a sub-pixel level.

Keywords: impervious surface; linear spectral mixture analysis; classification; land use; land cover.

Introduction

Impervious surfaces are defined as surfaces which water cannot infiltrate. These surfaces are primarily associated with transportation (streets, highways, parking lots, sidewalks) and buildings. Expansion of impervious surfaces increases water runoff, and is a primary determinant of storm-water runoff volume, water quality of lakes and streams, and stream habitat quality in urbanized areas. Increases in impervious surfaces, and accompanying phosphorous, sediment and thermal loads, can have profound negative impacts on lakes and streams and habitat for fisheries. The percentage of impervious surface area has emerged as a key factor to explain and generally predict the degree of impact severity on streams and watersheds. It has been generally found that most stream health indicators decline when the impervious area of a watershed exceeds 10 percent (Schueler, 1994). Arnold and Gibbons (1996) suggest that impervious surface area provides a measure of land use that is closely correlated with these impacts, and more generally that the amount of impervious surface in a landscape is an important indicator of environmental and habitat quality in urban areas. In the area of urban climate, Yuan and Bauer (2006) have recently documented a strong relationship between amount of impervious surface area and land surface temperatures or the urban heat island effect. It follows that impervious surface information is fundamental for watershed planning and management and for urban planning and policy. Continuing worldwide urban growth increases the amount of impervious surfaces of man-made materials, which change the hydrological properties of a watershed: instead of gently infiltrating, surface water eventually runoff to the rivers more quickly, picking up potentially polluting substances on its way. This in turn increases the risk for water pollution and floods in the watershed, thereby requiring the construction of expensive water purification systems, hampers the recharging of aquifers and increase erosion (Arnold and Gibbons, 1996; Schueler, 1994).

Mixed pixels are common problem in remotely sensed data because of limitations in spatial resolution of the data and the heterogeneity of features on the ground. The mixture spectra are often generated when the pixel covers more than one land-cover class. This problem often produces poor classification accuracy when conventional algorithms such as the maximum likelihood classifier (MLC) are used. In moist tropical regions, classification of stages of secondary succession (SS) is especially difficult because of its variations in vegetation stand structure, species composition and biomass (Mausel *et al*., 1993). However, it is possible to obtain better results if the mixed pixels are decomposed into different proportions of selected components. In order to solve the mixed pixel problem, scientists have developed different models to unmix the pixels into different proportions of end members (Ichoku and Karnieli, 1996). Linear spectral mixture analysis (LSMA) is one of the most often used methods for handling the spectral mixture problem. It assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel (Robert *et al*., 1998; Ustin *et al.*, 1998). LSMA is a physically based image analysis process that supports repeatable and accurate extraction of quantitative subpixel information (Adams *et al*., 1986; Smith *et al*., 1990; Roberts et al., 1998; Ustin *et al*., 1999). It has been used for vegetation or land-cover classification (Ustin *et al*., 1996; Cochrane and Souza, 1998; Aguiar *et al*., 1999; Petrou, 1999; Ustin *et al*., 1999; DeFries *et al*., 2000; Ustin and Xiao, 2001; Theseira *et al*., 2002) and for change detection (Adams *et al.*, 1995; Roberts *et al*., 1997; Roberts *et al*., 1998; Elmore *et al.*, 2000; Rogan *et al*., 2002).

Remote Sensing (RS) and Geographic Information System (GIS) are now proving to be useful tools for advanced ecosystem management. The collection of remotely sensed data facilitates the synoptic analyses of Earth - system function, patterning, and change at local, regional and global scales over time. Such data also provide an important link between intensive, localized ecological research and regional, national and international conservation and management of biological diversity (Wilkie and Finn, 1996).

Therefore, attempt has been made in this study to map out the impervious surfaces of Mubi town with a view to detecting the changes that occurred over time and the effect that have taken place particularly in the urban centers. This is in order to create possible solutions that might help in the future planning of the town using both Geographic Information System and Remote Sensing techniques.

Mubi town as a geo-political area falls within two Local Government Areas; Mubi North and Mubi South LGAs. The town is located between latitudes 10° 05’ and 10° 30'N of the equator and between longitude 13° 12' and 13° 19'E of the Greenwich meridian. The two Local Government Areas occupy a land area of 192,307 kilometer square and support a total population 260,009 people (National Population Census 2006). The area shares common boundary with Maiha Local Government Area in the South, Hong Local Government Area in the West, Michika Local Government Area and The Cameroon Republic in the East. (Figure 1.0 and 2.0).The growth of Mubi town is linked to the agricultural, administrative, and commercial functions it performs. By 1902, Mubi was a German base from where the neighboring tribes (i.e Fali, Gude, Kilba, Higgi, Margi and Njanyi) of the region were subjugated. On the 1st April 1960, Mubi was made a Native Authority Headquarters. The same year, July 1960, the town became a provincial headquarters of the defunct Sardauna province. In 1967, Mubi was made Local Government Area headquarters while in 1996, the town was splint into Mubi-North and Mubi-South Local Government Areas .Currently, the town is the seat of Mubi Emirate Council and the headquarters of Adamawa - North Senatorial District.

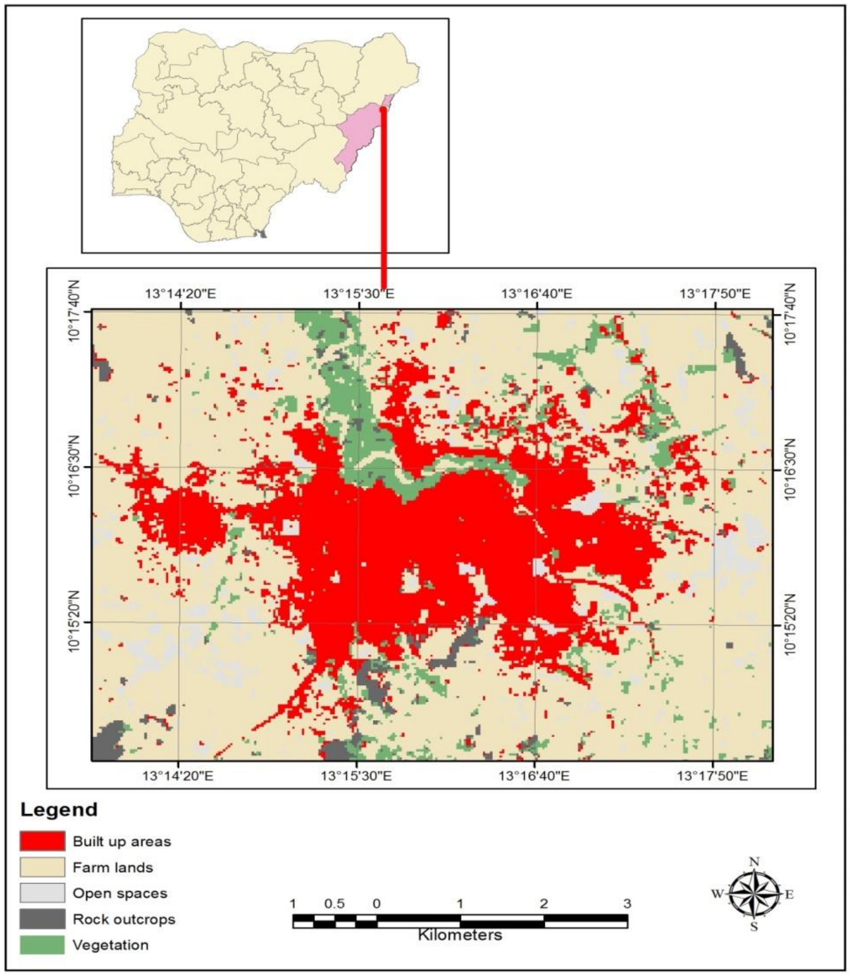

Figure 1: The Study Area

Materials and Methods

In this study, the utility of linear spectral mixture analysis (LSMA) is examined in a sub-pixel analysis of Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus imagery to map urban physical components in Mubi town. The three physical components of urban land cover (LC): impervious surface, vegetation and soil, were used in the LSMA. LSMA decomposes each pixel to address the heterogeneity of urban LC characteristic by allowing the number and types of end members to vary on a per pixel basis. This study generated spectral mixture models of 2-, 3-, and 4-endmembers for each pixel to estimate the fractions of impervious surface, vegetation and soil in the study area with a constraint of lowest root mean square error (RMSE). An analysis of the impervious surface areas (ISA) mapped with LSMA demonstrated that it produced more accurate results of mapping urban physical components. With the multilayered nature of Landsat TM data, quantification of sub-pixel percentage (%) of ISA and the % ISA changes was made to assess urban growth in the Mubi town, during the past twenty five years. The experimental results demonstrate that the LSMA approach is effective in mapping and monitoring urban land use/land cover changes using moderate-resolution multispectral imagery at a sub-pixel level.

Results and Discussions

Remotely sensed data provide a means for monitoring changes in urban land cover over time. Two scenes of the study area that were cloud-free or had low amounts of clouding were selected from

Landsat-7 TM images, acquired on March 18, 1987 and February 15, 2012. In order to validate the spectral unmixing results, references images comprising of 1-m spatial resolution Quickbird image, acquired on September 19, 2010, were selected as reference images to compare with the ETM+ image acquired in 2012.

Model calibration sites were randomly selected and high resolution quickbird image was used to determine the amount of impervious surface within each calibration site. Approximately, sites distributed across the image were collected for each image. Impervious surface area was determined from the 2009 1-meter resolutions quickbird image. Percent impervious surface area was calculated for each site by digitizing impervious surface within the site. The measurements of impervious surface area from the calibration sites were used to develop a principal component analysis relating percent impervious to the Landsat. As adopted in Crist and Cicone, (1984) responses for each of the summer Landsat images. Greenness is sensitive to the amount of green vegetation and therefore is inversely related to the amount of impervious surface area. An independent sample of approximately 25 accuracy assessment sites were selected from each of the Landsat images to measure the accuracy of the Landsat-derived impervious surface estimates. The sites were randomly selected and compared with high resolution Quickbird image.

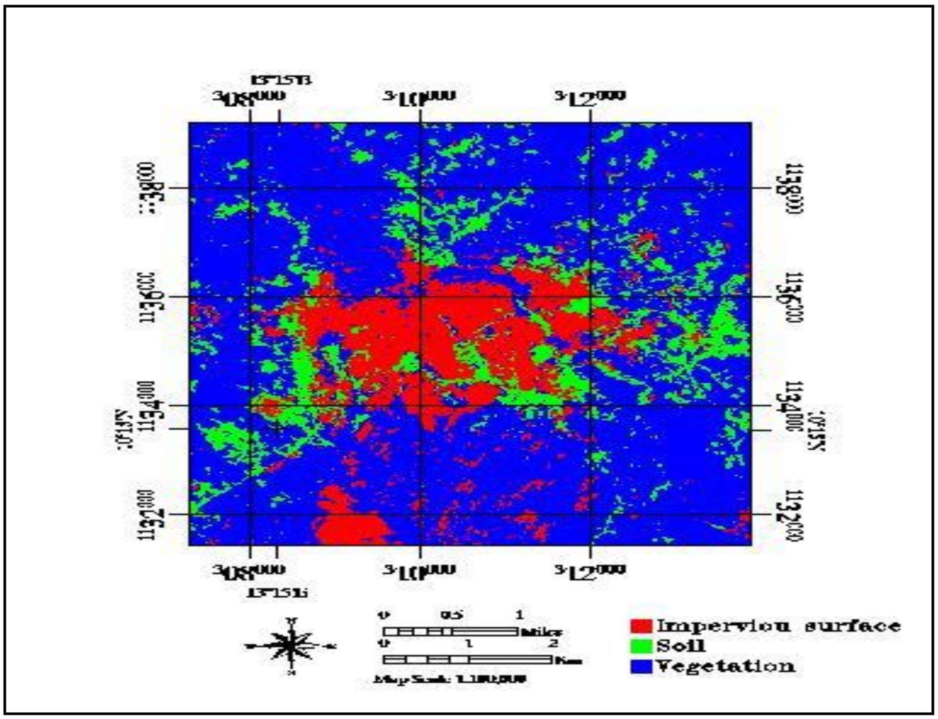

Figure 2: Map of the classified image showing studied area of 1987

Figure 2 shows the classified image of the study area depicting the area cover for each class, the area cover for impervious surface for the year 1987 is 10.34 Km² while soil covers 6.97 Km² and vegetation covers35.72 Km², it was discovered that in the year 1987, the impervious surface is smaller compared to that of the preceding year. Impervious surface is represented in red color, soil in green color and blue depicts vegetation.

Table 1: showing the percentage and area of change in the year 1987

Class Distribution	**Color and Pixel values**	**Percentage**	**Area**
Impervious surface	[Red] 2414 points: 10,268 points	(16.342%)	(10.3402 Km²)

Soil	[Green] 347 points: 8,585 points	(13.663%)	(6.9732 Km²)
Vegetation	[Blue] 1691 points: 43,979 points	(69.995%)	(35.7219 Km²)

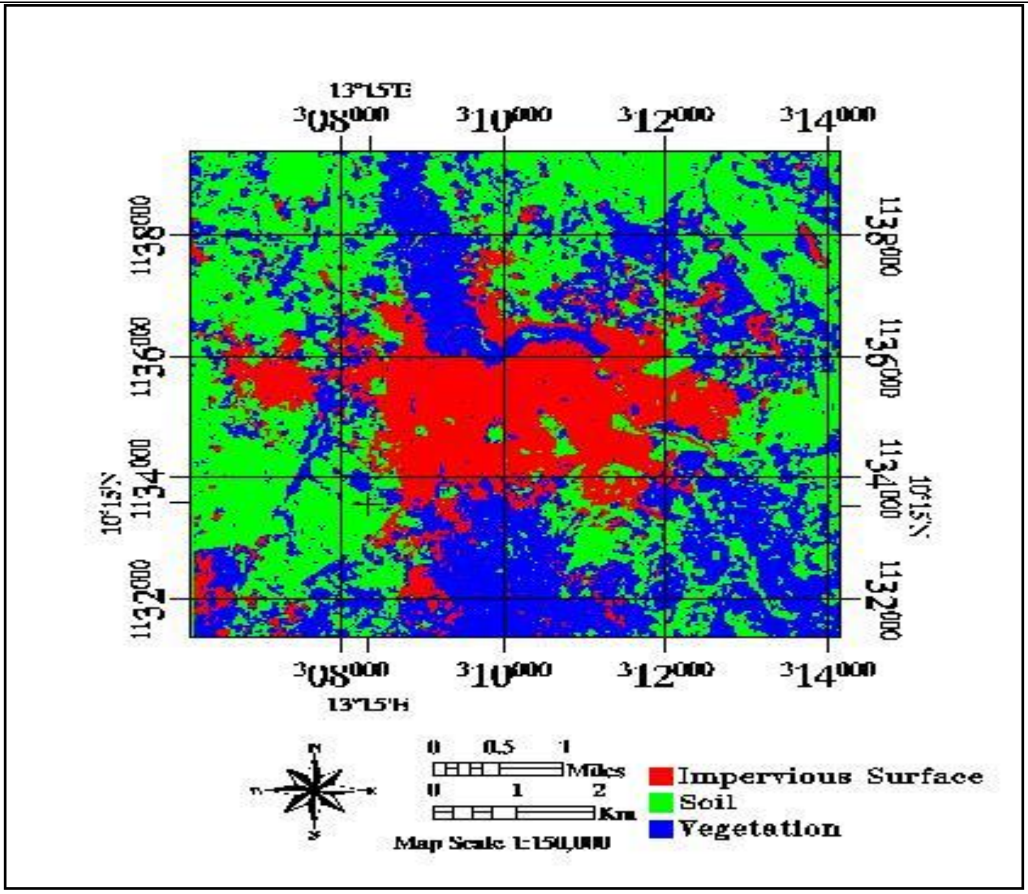

Figure 3: showing change image of 2012

Figure 3 shows the classified image of the study area depicting the area cover for each class, the area cover for impervious surface for the year 2012 is 12,705.2 Km² while soil covers 22,567.0 Km² and vegetation covers18, 608.8 Km², it was discovered that in the year 2012, the impervious surface has increased compared to that of the 1987. Vegetation has given way for impervious surface and bare land (Soil).

Table 2: showing percentage and area of change image of 2012

Class Distribution	**Color and Pixel values**	**Percentage**	**Area**
Impervious Surface	[Red] 4115 points: 15,228 points	(21.124%)	(12,705.2 Km²)
Soil	[Green] 430 points: 30,630 points	(42.489%)	(22,567.0 Km²)
Vegetation	[Blue] 691 points: 26,232 points	(36.388%)	(18,608.8 Km²)

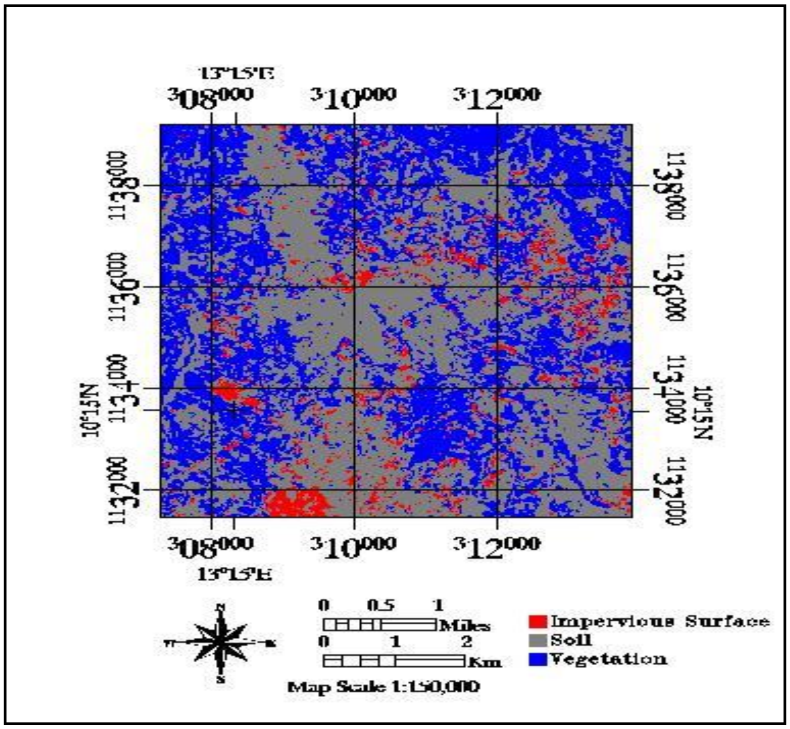

Figure 4: showing the changes in 1987 and 2012

Table 3: percentage statistical changes between 1987 and 2012

Percentages Changes between 1987 and 2012 image Statistics					
Impervious Surface	76.480	29.517	11.283	100.000	100.000
Soil	4.538	53.221	40.533	100.000	100.000
Vegetation	18.981	17.263	48.184	100.000	100.000
Class Total	100.000	100.00	100.000	0.000	0.000
Class Changes	23.520	46.779	51.816	0.000	0.000
Image Difference	**49.484**	**166.29**	**- 44.014**	**0.000**	**0.000**

The classified image of magnitude and direction with reference to the years 1987 and 2012 (Figure 4) highlights an intensive dynamics related to the different classes during this periods characterized by the increase of impervious and decrease in vegetation cover in the study area. The change image as presented in Table 3 shows that the impervious surface class covers about 23.520% of the total area. Meanwhile the soil and vegetation classes cover 46.779% and 51.816% respectively. This indicates the trend of increasing impervious surface and soil in the study area during this period.

Table 4: Area cover changes between 1987 and 2012

Area in (Square Km) Changes between 1987 and 2012 image Statistics					
Impervious Surface [Red] 4115 points	6.38	2.06	4.03	12.47	12.47
Soil [Green] 430 points	0.38	3.71	14.48	18.57	18.57
Vegetation [Blue] 691 points	1.58	1.20	17.21	20.00	20.00
Class Total	8.34	6.97	35.72	0.00	0.00
Class Changes	1.96	3.26	18.51	0.00	0.00
Image Difference	4.13	11.60	-15.72	0.00	0.00

Qualitative changes in the impervious fractions are visually interpreted by displaying fractions and colours for year 1987 and year 2012 (Figure 4). The visual interpretation of colour composite imagery shows that the major changes have the most saturated colours impervious in red, soil in ash and vegetation in blue colour while minor changes have less saturated colours.

The driving forces of impervious surface in the study area

Driving forces are factors that cause change in the phenomenon of spatial features and are influential in the evolution processes of the land surfaces (Burgi, *et al*, 2004). Spatial change, such as impervious surface is a consequence of natural, socioeconomic, political, and technological factors that drive and influence the development of spatial structure of a place (Burgi *et al*., 2004). Researchers in various fields of studies have categorized the different driving forces of Land Cover Change into various types based on the purpose and case being studied. Understanding the fundamental types of the driving factors is one of a basic requirement to identify the most important drivers of change to develop realistic models of Land Cover Change (Veldkamp & Lambin, 2001).

According to Burgi *et al*. (2004), the driving factors can be identified as: (1) environmental factors; (2) local scale neighbourhood factors; (3) spatial factors (accessibility); (4) level of economic development; and (5) urban and regional planning policies, which can be further categorized as site characteristics, neighbourhood characteristics, and proximity characteristics.

Impervious surface in Mubi town can be attributed also to several biophysical, socio-economics, and management system. In the first instance population dynamics are the most significant driving factor of Land Cover Change (urban expansion) in the town. The rural-urban migration and the natural fertility rate have stimulated urban spatial development and business, leading to rapid environmental changes (NEMA, 2009). Policies for the economic transformation in the country declares Mubi town as center for economic development through commercial activities which is the second main driving forces of the urban expansion. Associated with economic transformation, several driving forces such as market forces, commodification of land and informalization of the land acquisition has been the conversion factors of environmentally sensitive land in the urban area (ASUPDA, 2009). Apart from these, Land Cover Changes in the town are also initiated by the development of various new infrastructures across the town. For instances, the construction of roads in the town have made boundless contributions to the degradation and consequent cementing of the surrounding natural environments.

Conclusions

Spatial data and multi-temporal analysis of remote sensing data were allocated to understand the phenomena of impervious surface in the study area. LSMA technique was adopted to map and analyze the impervious surface using the above mention data. Combinations of multispectral mixture analysis of Landsat imagery and field observations as well as human activities examined and enlightened the nature and causes of impervious surface processes in the study area in the years 1987 and 2012. Mubi town, like many towns, is characterized by a sign of heterogeneity of land use/land cover. The relationships between man, vegetation, soil and environment, as determinant factors for dynamics of impervious surface in the study area, were analyzed and discussed. LSMA results show a noticeable significant decrease in vegetation fraction in 1987 and 2012. This concludes that impervious surface can be recognized by reduction of total vegetation cover and exposure of bare sand soil. The results emphasized the phenomena of deforestation in the addressed periods. Increasing in population during the study period is mainly attributed to increasing of impervious surface in the study area. The results generated from LSMA of Landsat imagery prove the viability of such method in mapping impervious surface in relation to mismanagement of land use in the study area. This concludes that LSMA applied to Landsat imagery such as TM and ETM+ is an efficient technique in mapping impervious surface in urban areas and its results can be generalized successfully. Statistical analysis of LSMA results shows high significant difference in impervious surface, vegetation, and soil fractions throughout the addressed periods (1987and 2012). CVA maps the impervious surface areas and proves the increase of such areas from 1987 to 2012 as well the decrease of them from 1987 to 2012 in vegetation. Furthermore, it is well argued that human activities such as over-grazing, over-cultivation and tree cutting contribute highly to the impervious surface in the study area. The results of LSMA and visual interpretation supported by the field observations characterized and mapped the extension of increase human activities in the study area. These findings verified and answered the enquiry raised by this study about the efficiency of LSMA in detecting and mapping impervious surface in the study area.

Recommendations

Intensive land use, such as in Mubi town, obviously accelerates deforestation and land degradation processes. The decrease in vegetation cover simultaneously with increasing exposure of soil surface will certainly increase runoff and erosion in the study area. Despite of this severe problem, efforts should be exerted to study and assess impervious surface in Mubi town as well as in regions in order to mitigate this problem. Based on the findings under the above mentioned limitations the study reached to the following recommendations:

• Application of remote sensing as accurate, low-cost and safe techniques to assess and

Mapping impervious surface areas provides valuable information on suitable land use/land cover management to conserve the natural resources in the study area.

• Training and rising of building capacity of researchers in application of remote sensing in environmental and natural resource management.

• Application of remote sensing in extensive focus (*in situ*) LULC areas is more effective than widespread global one.

• Using of high resolution and more advanced remote sensing data as hyperspectral one for monitoring LULC and land degradation.

• Establishment of more extensive regional monitoring network to collect baseline data relevant to all aspects of impervious surface specifically in the study area and Adamawa state in general.

• Establishment of shelterbelts and windbreaks by cultivating suitable species such as *Maeruacrassifolia*, *Leptadena pyrotechnica* and *Acacia tortilis*to avoid the erosion and to protect the study area from deforestation and degradation.

• To reduce impact of human activities on vegetation, restoration and re-vegetation programs around the settlements is well recommended especially in the areas which are subjected to sever agricultures activities.

• To resolve farmer-nomads tension, integration of rural communities in management of agricultural projects.

• Rationalization of policies towards more conservation programs for rehabilitation of degraded areas.

• Improvement and management of the human activities.

• Construction and maintenance of water channels in the study areas.

• Enhancement of rehabilitations programs by urban planners administration sector to protect the natural environment in the area with more emphasis on community participation.

References

Adams, J.B., Sabol, D.E., Kapos, V., Almeida R.F., Roberts, D.A., and Smith, M.O.,(1995). Classification of multispectral images based on fractions of end members: Application to land-cover change in the Brazilian Amazon. *Remote Sensing of Environment*, 52, 137-154.

Adams, J.B., and Smith, M.O.,(1986). Architecture: Shade and shadow in geobotanical mapping a(abs.), *Fifth Thamatic Conf., Remote Sensing for Expl. Geol.*, Vol.111 ERIM, Houston, TX.

Aguiar, A.P.D., Y.E. Shimabukuro, and N.D.A. Mascarenhas, 1999. Use of Synthetic bands derived from mixing models in the multispectral classification of remote sensing images. *International Journal of Remote Sensing*, 20 pp. 647 – 657.

Arnold, C.L., and Gibbons, C.J., (1996). Impervious surface coverage: the emergence of a key environmental indicator. *Journal of the American Planning Association* 62 (2), 243-258.

ASUPDA, (2009) Problems of Development Control in Mubi.

Burgi, M., Hersperger, A. M., & Schneeberger, N.

(2004). Driving forces of landscape change - current and new directions. *Landscape Ecology, 19*(8), 857-868.

Cochrane, M.A., and C.M. Souza Jr., 1998. Linear mixture model classification of burned forest in the eastern Amazon. *International Journal of Remote Sensing*, 19,pp. 3433 – 3440.

DeFries, R.S., M.C.Hansen, and J.R.G. Townshend, 2000. Global continuous Fields of vegetation characteristics: a linear mixture model applied to multi-year 8 km AVHRR data. International Journal of Remote Sensing, 21,pp. 1389 – 1414.

Elmore, A.J., Mustard, J.F., Manning, S.J., and Lobell, D.B., (2000). Quantifying vegetation change in semiarid environments: precision and accuracy of spectral mixture analysis and the normalized difference vegetation index, *Remote Sensing of Environment*,73 (1), 87-102.

Ichoku, C., and A. Karnieli, 1996. A review of mixture modeling techniques for sub-pixel land cover estimation. Remote Sensing Reviews, 13,pp. 161 – 186.

Mausel, P., Y. Wu, Y. Li, E.F. Moran, and E.S. Brondizio, 1993. Spectral Identification of Succession Stages Following deforestation in the Amazon. Geocarto international, 8,pp. 61-72.

National Population Census (2006), Nigerian States by Population, Retrieved 20th April 2010 from www.population.gov.ng

NEMA. (2009). Atlas of Our Changing Environment: National Enviornment Management Authority. http://www.grida.no/files/publications/uganda-atlas-2009.pdf

Petrou, M., 1999. Mixed pixel classification: an overview in: Information Processing for Remote Sensing, ed. C.H. Chen, World Scientific Publishing Co., Singapore, pp 69 – 83.

Roberts, D. A., Batista, G.T., Pereira, L.G., Waller, E.K., and Nelson, B.W.,(1998a). Change Identification Using Multitemporal Spectral Mixture Analysis: Application in Eastern Amazonia. In Lunetta, R.S., and Elvidge, C.D. (Eds.), *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications* (pp.137-161). Chelsea, Michigan: Ann Arbor Press.

Roberts, D.A., Gardner, M., Church, R., Ustin, S., Scheer, G., and Green, R.O., (1998b). Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models. *Remote Sensing of Environment*, 65,267-279.

Rogan, J., and Chen, D., (2003). Remote sensing technology for mapping and monitoring land-cover and land-use change; *Progress in Planning*, 61, 301-325. Rosso, P.H., Ustin, S.L., and Hastings, A.,(2005). Mapping marshland vegetation of San Francisco Bay, California, using hyperspectral data, *International Journal of Remote Sensing*, 26 (23), 5169-5191.

Schueler, T.R.,(1994), The importance of imperviousness. *Watershed Protection Techniques,* **1**, pp. 100-111.

Smith, M.O., Ustin, S.L., Adams, J.B., and Gillespie, A.R.,(1990). Vegetation in deserts: I. A regional measure of abundance from multispectral images. *Remote Sensing of Environment*, *31*, 1-26.

Theseira, M.a., G.Thomas, and C.A.D. Sannier, 2002. *An evaluation of spectral mixture modeling applied to a semi- arid environment*. International Journal of Remote Sensing, 23,pp. 687 – 700.

Ustin, S.L., Q.J. Hart, L. Duan, and G. Scheer, (1996). Vegetation mapping on hardwood rangelands in California. *International Journal of Remote Sensing*, 17, pp. 3015–3036.

Ustin, S.L., D.A. Roberts, and Q.J. Hart,(1998). Seasonal vegetation patterns in a California coastal savanna derived from Advanced Visible/Infrared Imaging Spectrometer (AVIRIS) data. In: *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications*, ed. R.S. Lunetta and C.D. Elvidge, Ann Arbor Press, Ann Arbor, Mich., USA, pp. 163–180.

Ustin , S.L., and Q. F. Xiao, 2001. Mapping successional boreal forests in Interior Central Alaska. *International Journal of Remote Sensing* . 22,pp. 1779 – 1797.

Veldkamp, A., & Lambin, E. F. (2001). Predicting land-use change. *Agriculture, Ecosystems & amp; Environment*, *85*(1–3), 1-6.

Wilkie, D.S. and Finn, J.T., 1996. Remote Sensing Imagery for Natural Resources Monitoring. *A* *guide for First-Time Users. Methods and Cases in Conservation Science Series*. Xxi+ 295.pp. New York, Chichester Columbia University Press.

Yuan, F., and Bauer, M.E., (2006). Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment*, 106 (3), 375-386.