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Research Article **Open Access**

Urban Built-up Area Extraction and Change Detection of Adama Municipal Area using Time-Series Landsat Images

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Abstract Urban built-up area information is required in various applications of land use planning and management. However, urban built-up area extraction from moderate spatial resolution Landsat time-series data is challenging because of significant intra-urban heterogeneity and spectral confusion between other landcover types. This paper proposes a technique to extract urban built-up area from time-series Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imageries and determines urban area changes between 1984 to 2015 of Adama Municipal Area of Ethiopia. The study selected three indices, the Enhanced Built-Up and Bareness Index (EBBI), Soil Adjusted Vegetation Index (SAVI) and Modified Normalized Difference Water Index (MNDWI), to represent three major urban land-use classes: built-up and barren/bare land, open waterbody, and vegetation, respectively. The built-up area was extracted by taking the difference between EBBI, SAVI and MNDWI to remove the vegetation and water noises, and the resulted index image was spectrally segmented to separate built-up area from the non-urban built-up lands. The derived index was used to map built-up area for 1984, 1995, 2005 and 2015 periods. The expansion of the built-up area has been revealed as a major change in the area when city area expanded substantially by 293% between 1984 to 2015 periods. The advantage of the method was to use almost the entire spectral range of Landsat imageries which cause less spectral confusion between land cover classes and hence resulted in higher accuracies compared to other indices. The method was effective and simple to implement, and can be used for built-up extraction in other areas.
Keywords *Remote Sensing; Built-up Area; Spectral Indices; Urban Study; Landsat*

1. Introduction

Like any other cities in the developing world, Adama city has been gradually expanding both physically and in terms of its population and has been the locus of economic activity and transportation nodes in Ethiopia. Urban areas are dominated by built-up lands with impervious surfaces (Xu et al., 2000). Since the expansion of urbanized areas results in encroachment of surrounding valuable natural lands, the conversion of the nature lands into impervious built-up area may have significant impacts on the ecosystem, hydrologic system and biodiversity in the area (Xu, 2007). The study of urban spatial expansion always needs accurate, quick and timely information on urban built-up areas in the form of size, shape, and spatial context for urban land use planners and decision makers. The information on pattern and extent of built-up area expansion in past few decades even becomes more important for various decision making process in terms of resource and utility allocation and distribution to attain urban landuse sustainability. Time-series satellite remote sensing data with different spatial and spectral resolutions have been found very promising to meet these requirements and have been used in several built-up area mapping and urban studies (e.g., Batty and Howes, 2001).

Mapping urban built-up areas using moderate resolution remote sensing data such as from Landsat TM/ETM+ data is complex because urban areas comprise of manmade and natural features like vegetation, waterbody, bareland etc. These urban areas often display heterogeneous spectral characteristics and significant spectral confusion between land cover classes and as a result reduce mapping accuracy. For example, barren land and asphalt concrete share similar spectral properties and, as a result, can be readily confused. To overcome this spectral confusion, numerous techniques have been developed for built-up and urban landcover mapping using satellite data. These techniques can be broadly grouped into two categories (He et al., 2010): (a) classification-based that involves use of different classification algorithms to improve mapping accuracies at pixel- and object-levels (e.g., Cleve et al., 2008) and (b) index-based that involve development of different indices to enhance a particular built-up area and determination of optimal threshold level to separate built-up areas from other landcover types (e.g., He et al., 2010; Zhang et al., 2005). Several indices for mapping the built-up and other landcover types in urban areas, such as the Normalised Difference Built-Up Index (NDBI) (He et al., 2010), Index-based Built-Up Index (IBI) (Xu, 2008), Urban Index (UI) (Kawamura et al., 1996), Normalised Difference Bareness Index (NDBaI) (Zhao and Chen, 2005), and Bare soil index (BI) (Rikimaru and Miyatake, 1997) have been employed in various studies. However, each has its own advantages and disadvantages. For example, NDBI and UI were used for mapping of built-up or bare land areas, however, they were found ineffective in differentiating built-up area from bare land areas (Zha et al., 2003; He et al., 2010; Sukristiyanti et al., 2007) and therefore the universality of the approach needed to be tested in other geographic areas. He et al. (2010) improved the accuracy of the original approach using the automatic segmentation method. They noted that the complex spectral response pattern of vegetation, bare land, and built-up areas resulted in spectral confusion between classes and hence made it difficult to separate them on NDBI image. Varshney (2013) improved this method by setting an optimal threshold value by allocating improved positive difference values of continuous NDBI and Normalized Difference Vegetation Index (NDVI) to built-up areas. Xu (2008) developed the index-based built-up index (IBI) to detect asphalt and concrete surfaces.

In this study, a new technique is applied for the extraction of urban built-up area from Landsat data based on new image derived from three thematic indices, Enhanced Built-Up and Bareness Index (EBBI) (As-syakur, 2012), Soil Adjusted Vegetation Index (SAVI) (Huete, 1988), and Modified Normalized Difference Water Index (MNDWI) (Xu, 2005). The method is demonstrated through the extraction of urban built-up area of Adama Municipality from Landsat TM/ETM+ images for 1984, 1995, 2005 and 2015, and identification of changes in built-up areas between 1984-2015 periods. The study is important because Adama city is characterized by low density and low-rise development and like any third world city, leap frogging and sporadic developments are common in Adama. Therefore, common built-up area mapping indices do not look very promising in this case and there is need to develop alternative built-up mapping method for such area. Further, excessive alteration of landuse has been taking place without formal procedures. Therefore, information on built-up area change spatially would allow urban planner and decision makers to understand and evaluate municipal growth pattern in relation to landcover changes and management for sustainable usage of invaluable nature lands.

2. Study Area

Adama Municipal Area (AMA) comprises of city area and its surrounding covering a total area of 43.2 square km and characterized by a very good agricultural land in the vicinity. Adama city is located in central Ethiopia about 100 km south east of country capital Addis Ababa at 8^{o}35$^{'}$ to 8^{0}36'N latitude and 39^{0}12'' to 39^{0}21'15"E longitude at an average altitude of 1620 m above sea level. It is situated in Rift valley system in the upper Awash River Basin. Figure 1 shows location map of the study area and Figure 2 shows urban built-up area for the year 1984 and 2005.

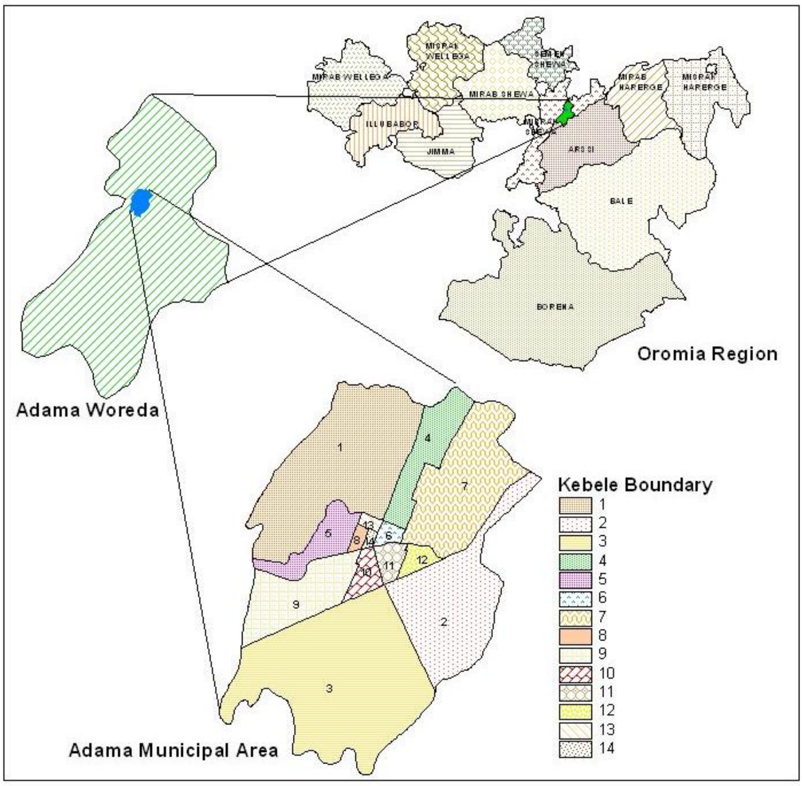

Figure 1: *Location map of the Adama Municipal Area with Kebele boundaries*

The urbanized area, which for many years was confined near and around the railway station, in the last three decades, has spread out in to the outer zones mainly to the southern fringes along the roads from Addis to the Awash. The area is covered by soil which is built up of light and fine clay which is easily blown in the storms during the dry months. The annual rainfall which mostly comes in the month of June-August ranges between 700-900 mm.

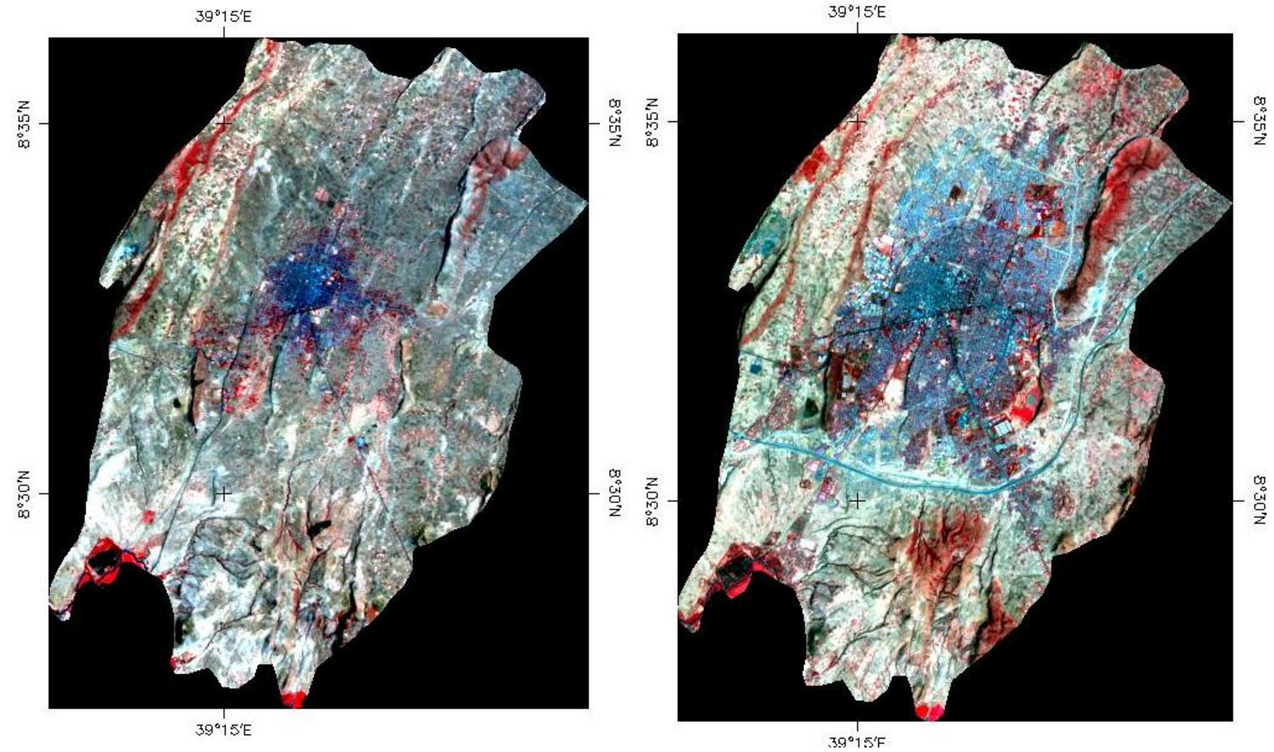

Figure 2: *Adama City area in the year for 1984 and 2015 as shown on Standard False Colour Composite (FCC) of Landsat images. (FCC bands R:G:B–4:3:2)*

3. Material and Methods

3.1. Image Acquisition and Pre-processing

Landsat time-series Thematic Mapper (TM) data of April 1984 and March 1995 and Enhanced Thematic Mapper plus (ETM+) data of January 2005 and February 2015 (path 168, row 54) – were acquired for built-up area extraction and change detection for the study. All image processing tasks were implemented in ENVI 5.0. The purpose of image pre-processing was to make all of the images similar so that they can be considered to be taken at the same environmental conditions, and by the same sensors (Hall et al., 1991). In the current study, the images were geometrically referenced to the UTM Zone 37 N projection system. Conversion of digital numbers (DNs) into radiance or surface reflectance is a requirement for quantitative analysis of multiple images acquired on different dates (Lu et al., 2004; Sinha et al., 2012). All four image DNs were converted to top-of-atmosphere (TOA) reflectance values using the equation suggested by Chander and Markham (2003). Further, a linear regression method was adopted for normalizing images on two different dates assuming the image pixel values on date 1 to be a linear function of the values of the same area on date 2 (Eckhardt et al., 1990; Jha and Unni, 1994).

3.2. New Built-Up Index (NBUI)

The concept of NBUI is based on the understanding that the urban area is a complex ecosystem composed of four main heterogeneous components: impervious surface material, green vegetation, exposed soil or bare soil and waterbody. Therefore, NBUI applies almost the entire wavelengths of Landsat images to represent these major urban landuse classes and computed as:

$$NBUI = \frac{B5-B4}{10*\sqrt{B5+B6}} - \left(\frac{(B4-B3)*(1+l)}{B4-B3+1} + \frac{B2-B5}{B2+B5}\right) \quad (1)$$

where l = 0 to 1 depending upon high density vegetation (l = 0) to low density vegetation (l = 1). The first part of equation 1 uses near-infrared (NIR) (0.83 μm), shortwave-infrared (SWIR) (1.65 μm), and thermal-infrared (TIR) (11.45 μm) of Landsat images to highlight the contrast reflection range and absorption in built-up and bare land areas (e.g., Chen et al., 2003; Zha et al., 2003). The second part of NBUI uses SAVI to highlight vegetation by taking ratio of NIR (B4) to a red (B3) band to take advantage of high vegetation reflectance in NIR and high pigment absorption of red light (Jensen, 2007). The study used SAVI to map vegetation in place of commonly used Normalized Difference Index (NDVI) due to its advantage over NDVI when applied in an area with low plant cover such as the Adama Municipal Area. The SAVI was found effective even in area with vegetation cover as low as 15 percent, while NDVI is effective in area where vegetation cover is above 30 percent (Ray, 1994). The final expression of NBUI is used to map water, a major component in urban landuse, using a SWIR (B5) and green band (B2) as suggested by Xu (2005). Finally, density slicing was carried on NBUI image to create binary images separating built-up area from other landcover types for the year 2005 (Sinha and Kumar, 2013; 2014). The process was repeated for other change years (1984, 1995 and 2015) and the extracted built-up areas were compared to determine the change. To compare the effectiveness of NBUI in built-up area extraction, the results were compared with other commonly used built area mapping indices such as the Normalized Difference Built-up index (NDBI) (Zha et al., 2003) and Urban Index (UI) (Zhang et al., 2013) computed as:

$$NDBI = \frac{B5-B4}{B5+B4} \quad (2)$$

$$UI = \frac{B7-B4}{B7+B4} \quad (3)$$

3.3. Accuracy Assessment

High resolution IKONOS image (4 m spatial resolution) of Adama city for the year 2005 was used to assess the accuracy of extracted built-up area from different indices. The extracted built-up binary images were overlaid on the IKONOS image, and then visually inspected on pixel basis. The built-up areas were vectorized based on visual interpretation of IKONOS image, which was then converted into 30 × 30 m pixels in raster form in order to compare the results. A random sampling technique was applied to collect 75 sample pixels to compare the accuracies of built-up extraction from different indices and to evaluate the difference between them. The mapping accuracies were reported in the form of overall accuracy (OA) and kappa coefficient (κ) (Congalton and Green, 2009).

4. Results and Discussion

The mean spectral response of four landcover classes (Built-up, vegetation, barren land and waterbody) of Adama municipal area is shown in Figure 3.

Values area derived by taking mean of 20 pixels for each class.

It can be seen that built-up areas reflectance to be higher at SWIR and TIR wavelengths (B5, B6-1,2) and low in NIR (B4), and therefore these band associated with a high contrast for detecting built-up and bare land areas. Further, there exists an inverse reflectance relationship in B4 and B5 between built-up or bare land areas and vegetation. Vegetation has a high reflectance in B4 than the reflectance of built-up or bare land, while in B5 the reflectance of built-up is higher than vegetated areas (Herold et al., 2003). The TIR band has ability to distinguish high and low levels of albedo in built-up objects (Zhao and Chen, 2006), which can be used for mapping built-up areas based on a low albedo, which eliminates the effect of shadows and water while high albedo demonstrates built-up and bare land (Weng, 2008). The use of SWIR in this study in place of NIR band in commonly used normalized difference water index (NDWI) is due to high built-up area reflectance in SWIR compared to NIR. Thus the resulting index will have negative values for the built-up area and positive values for the water features, which makes water features free from built-up area noise on index image. The index will not impact on vegetation due to negative value for vegetation. Therefore, by taking difference between index highlighting built-up area and bare land with indices highlighting vegetation and water as shown in equation 1, will result in positive values for built-up and barren pixels and will result in negative values for vegetation and water.

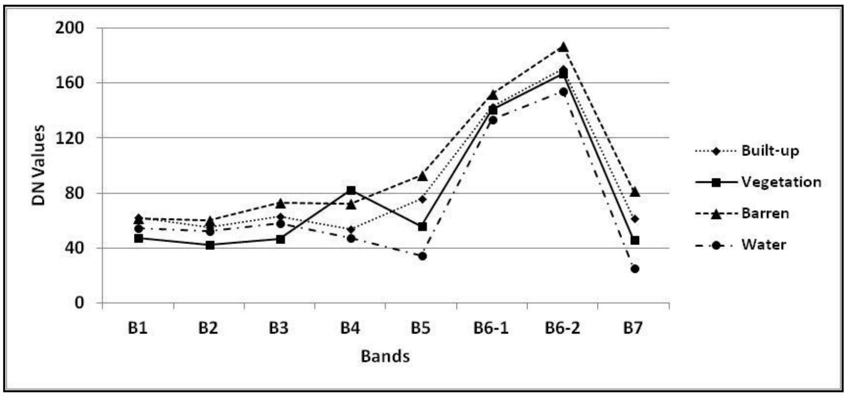

Figure 3: *Spectral profiles for four land cover classes of Adama Municipal area for the year 2005*

Figure 4 shows the built-up area extracted from NBUI (proposed method) and the two commonly used built-up indices, normalized difference built-up index (NDBI) and the urban index (UI) for the year 2005. The patterns of built-up area extraction were found similar in the three cases, however, the built-up area were more in case of NDBI and UI compared to NBUI. This is because of inability of NDBI and UI to differentiate between built-up and barren land or bare soil and most of the barren area in the adjacent land got mixed with the built area. However, high spectral reflectance of built-up area in B5 than vegetated areas and the ability of TIR band to distinguish high and low levels of albedo in built-up objects allowed built-up area to be separated from barren land in NBUI image. Further, by taking the difference between index highlighting built-up area and bare land and vegetation and water indices, separated built-up area from vegetation and water, resulting in higher accuracy in case of NBUI. The overall accuracy (OA) and kappa for NBUI image in built-up area extraction was found to be 93.2% and 0.91, respectively, which was much higher than NDBI (OA = 88.4%, kappa = 0.86) and the UI (OA = 86.1%, kappa = 0.83) images. The built-up areas as determined by each remote sensing indices and from the IKNOS data for the year 2005 were compared to determine the difference in area accuracies. The analysis results showed that the total built-up area obtained from the NBUI was 1074.6 ha, which was 124.5 ha more than the area determined from the IKONOS imagery. However, the built-up area extracted from the other two indices NDBI and UI were much higher (378.3 ha and 412.5 ha, respectively) as compared to IKONOS image based built-up area.

4.1. Built-Up Area Expansion from 1984 to 2015

The proposed method (NBUI) was most accurate in terms of built-up area extraction as compared to other two indices, and hence was used for built-up area mapping for the years 1984, 1995 and 2015, which were then compared to determine the built-up area expansion between 1984–2015 periods. Figure 5 shows built-up area expansion map highlighting the change occurring between two dates.

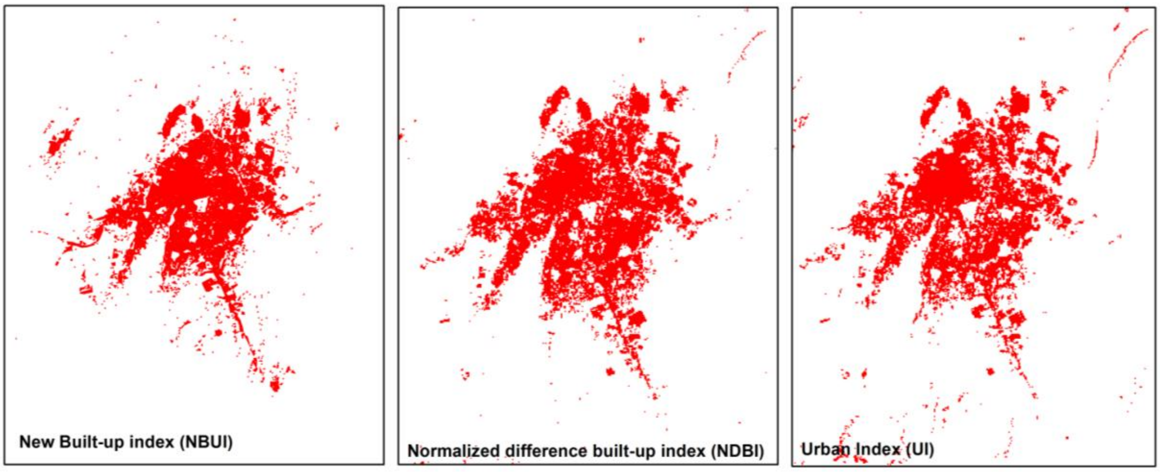

Figure 4: *Built-up area extracted for Adama Municipal Area from NBUI (proposed method) and the two commonly used built-up indices, normalized difference built-up index (NDBI) and the urban index (UI) for the year 2005*

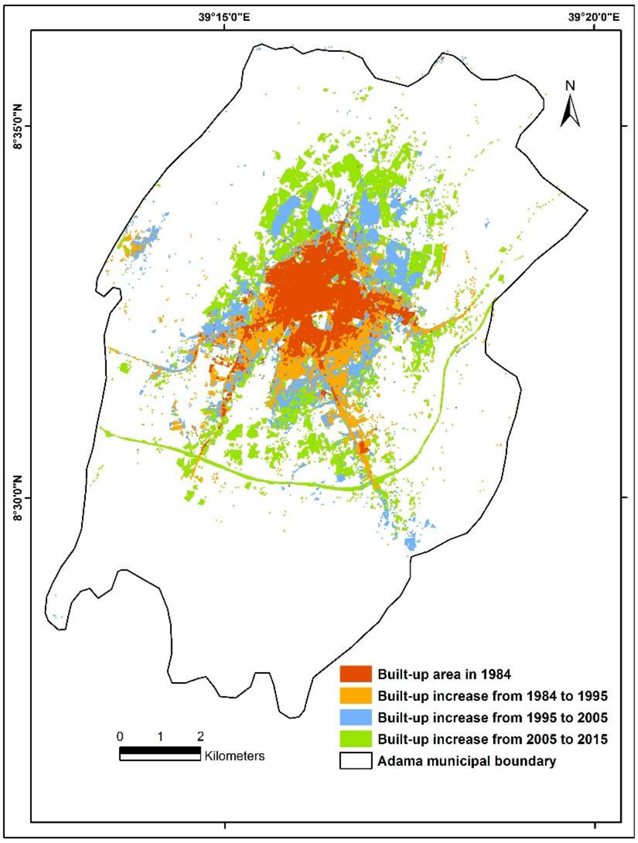

Figure 5: *Built-up area expansion from 1984 to 2015 in Adama Municipal Area extracted from the proposed method (NBUI). Different shades of colour highlighting the change occurring between two dates*

The comparison of class statistics shows that there has been marked land cover change in a span of 32 years. However, the results show a substantial increase in only two land use classes namely built up area and sparse vegetation. Built-up area showed an overall increase of almost 293% in a span of 32 years. The increase however was significantly higher (67.52 %) in the first decade of our study period, i.e. between 1984-1995. The increase in built-up area between 1995-2005 and 2005–2015 were also very significant (38.62% and 30%, respectively). The statistics for year 1984 shows city area to be spread in only 578 ha which was only 4.23 % of the total municipal area, which increased to 2275 ha by the year 2015 accounting for nearly 17% of the total area. The increase in city area spread over the years was mostly on barren land concentrated towards the northern and western part of the area. The rest of the region depicted dispersed built-up land patterns.

5. Conclusions

Remote sensing based indices in urban areas are generally used to distinguish different urban landuse features such as built-up, barren land, vegetation and waterbody. However, accurate extraction of these landuse features is very challenging because of high intermixing between classes, especially in urban areas. This study proposed a method (NBUI) that highlights built-up area by first highlighting built-up and barren land area based on information from near-infrared, shortwave-infrared and thermal infrared data, and then excluded the vegetation and water noises to extract built-up area. The index was applied in Adama municipal area, Ethiopia, to map built-up area from time series data from 1984 to 2015. The results obtained by the NBUI were compared with those from commonly used built-up indices, the NDBI and UI and improvement in accuracy was found in case of NBUI over the two in terms of built-up area extraction. The method was found very simple to compute and easy to implement, however, it needs more testing particularly for more complex heterogeneous landscapes in terms of differentiating landcover classes. It can be used as one of the spectral bands along with original bands, or with other indices to improve the classification accuracy which warrant subsequent study. In a period of 32 years (1984-2015), the built-up area in Adama municipality has increased almost by 293% which showed excessive alteration of landuse occurring in the area. The results from this study on built-up area change would allow urban planner to understand and evaluate municipal growth for sustainable usage of urban land system.

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