Data Article

Data on land use and land cover changes in Adama Wereda, Ethiopia, on ETM+, TM and OLI-TIRS landsat sensor using PCC and CDM techniques

A.S. Mohammed Abdul Athick a, K. Shankar b, *

a Department of Geomatics Engineering, School of Civil Engineering and Architecture, Adama Science & Technology University, Ethiopia
b Department of Applied Geology, School of Applied Natural Science, Adama Science & Technology University, Ethiopia

A R T I C L E   I N F O

Article history:
Received 7 February 2019
Received in revised form 17 March 2019
Accepted 20 March 2019
Available online 28 March 2019

Keywords:
Land use and land cover (LULC)
Change detection
Remote sensing
Landsat sensors
Post classification comparison
Change detection matrix

A B S T R A C T

Land use and land cover changes are often referred for the anthropogenic modification of Earth’s surface. The extents of land use and land cover (LULC) changes in Adama Wereda at three different periods (2002, 2010, and 2017) were generated using data from various Landsat sensors namely ETM+, TM and OLI TIRS. This work focused on a change detection analysis using post classification comparison (PCC) and change detection matrix (CDM). These images were geometrically corrected and image processing operations for instance: radiometric correction, using spectral radiance model was carried out, followed by land cover categorisation into water bodies, built up, bare land, sparse vegetation and dense vegetation employing Knowledge, pixel and indices based classification in ERDAS imagine software. The generated data of both change detection techniques from 2002 to 2017 revealed interesting aspect that build up, dense vegetation and sparse vegetation increased in area of approximately 160%, 30% and 78% respectively at the expense of barren land which decreased at 8.5%, but there is not much change in the water bodies. It was also noticed that both the algorithms gives similar values but with negligible deviation.

© 2019 Published by Elsevier Inc. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
1. Data

The data in this article depicts the status of LULC changes in Adama Woreda over three different periods 2002, 2010 and 2017. The administrative centre of Adama Woreda is Adama City. Fig. 1 – 3 illustrates five different LULC classes (built up, water bodies, dense vegetation, sparse vegetation and barren land) for the given period. In 2002 majority of the land cover was occupied by bare land around 80409.58 ha and the least was built up closer to 2034.34 ha. Whereas, in 2017, barren land reduced by 10575.58 ha and interestingly built up area expanded approximately 3208.56 ha. These are followed by Table 1. The data in table provides the information on area (ha) and percentage (%) occupied by five land use categories over time. Table 2 – 4 represents the producer accuracy of classifications. Fig. 4 shows the comparison of overall land use and land cover values in percentage. Figs. 5 and 6 illustrates the generated map by PCC for 2002 to 2010 and 2010 to 2017 respectively illustrating the changes from one feature to another. The data in Tables 5 and 6 demonstrates the change area in hectare generated by change detection matrix.

2. Experimental design, materials, and methods

Land use and land cover changes have major impact on wide range of environmental and landscape attributes [1]. ETM + (2002), TM (2010) and OLI – TIRS (2017) Landsat images of 30 m spatial resolution with path and row of 168/54 and GPS ground coordinates were the vital data employed in this article [2–6]. At first, all the data were radiometrically corrected to remove noise due to sensor and atmosphere using spectral radiance model. The spectral reflectance values from the spectral library were utilized to identify the features from images. The generated corrected images were enhanced and the surface features for instance built up, water bodies, dense vegetation, sparse vegetation and barren
Fig. 1. LULC classes of Adama Wereda in 2002.
Fig. 2. LULC classes of Adama Wereda in 2010.
Fig. 3. LULC classes of Adama Wereda in 2017.
land as defined by US geological survey [7,8] employing pixel, knowledge and indices based maximum likelihood classification. Indigenous features namely water bodies and vegetation were extracted using mathematical indices, features in mixed pixels were categorized by knowledge based classification and various features such as road network, settlements, industries, utilities under the category of built up were isolated by pixel based classification. The classified images were evaluated through confusion matrix, if the accuracy of the classified image accounted less than 80% then the images must be reclassified [9]. Finally, only the images with accuracy greater than 80% were used to generate land use and land cover changes by employing PCC and CDM techniques. The land cover changes for 2017 were validated by ground truth using GPS coordinates of sample spatial features with minimum 20 spatially distributed ground control points. For the images of 2002 and 2010 the area change was correlated by

| LULC Class                      | 2002    | 2010    | 2017    | 2002–2010 | 2010–2017 | 2002–2017 |
|---------------------------------|---------|---------|---------|-----------|-----------|-----------|
|                                 | ha      | %       | ha      | %         | ha        | %         |
| Sparse vegetation               | 5968.13 | 5.97    | 10602.67| 10.57     | 11980.2   | 11.97     |
| Dense vegetation                | 3592.75 | 3.59    | 4689.035| 4.65      | 4866.57   | 4.86      |
| Bare land                       | 80409.58| 80.37   | 73623.8 | 73.65     | 69834     | 69.80     |
| Water body                      | 8040.58 | 8.04    | 8249.94 | 8.25      | 8121.71   | 8.12      |
| Built up                        | 2034.34 | 2.03    | 2879.91 | 2.88      | 5242.9    | 5.24      |
| Total                           | 100045.38| 100     | 100045.38| 100      | 100045.38 | 100       |

Positive sign means increase while negative sign means decrease in area.

| Data                            | Bare land | Dense vegetation | Sparse vegetation | Water bodies | Built up | Row total % |
|---------------------------------|-----------|------------------|-------------------|--------------|----------|-------------|
| Bare Land                       | 483237    | 2                | 0                 | 1093         | 3457     | 487789      | 99.07 |
| Dense Vegetation                | 0         | 29246            | 504               | 6            | 0        | 29756       | 98.29 |
| Sparse Vegetation               | 2255      | 877              | 33259             | 375          | 16       | 36782       | 90.42 |
| Water Bodies                    | 0         | 0                | 0                 | 195786       | 0        | 195786      | 100   |
| Built Up                        | 7939      | 16               | 35                | 78           | 40368    | 48426       | 83.34 |
| Column Total                    | 493431    | 30141            | 33798             | 197338       | 43831    | 798539      | 100   |

Overall accuracy for 2002 classified image is 94.22%
using spatial link with google earth. The generated data from PCC and CDM depicted that built up has drastically increased from 2.03% to 5.24% and Bare land decreased from 80.37% to 69.80%. Moreover there was fluctuation in the area of dense and sparse vegetation approximately by 1.3% and 6% respectively. As Adama being a high elevated land the type of green cover on the ground has an effect on triggering or preventing natural hazards. If there are bushes or tree species can prevent and stabilize the highlands [10]. There is no significant change observed in water bodies.

Fig. 5. LULC transformation with respective codes using PCC technique (2002–2010).
Fig. 6. LUJC transformation with respective codes using PCC technique (2010–2017).
Table 3
Contingency Matrix of classified image, 2010.

| Data                | Sparse vegetation | Dense vegetation | Bare land | Water bodies | Built up | Row total | %     |
|---------------------|-------------------|------------------|-----------|--------------|----------|-----------|-------|
| Sparse Vegetation   | 21206             | 115              | 946       | 299          | 585      | 23151     | 91.6  |
| Dense Vegetation    | 76                | 1506             | 0         | 11           | 0        | 1593      | 94.54 |
| Bare Land           | 731               | 0                | 18622     | 73           | 920      | 20346     | 91.53 |
| Water Bodies        | 0                 | 0                | 36755     | 0            | 36755    | 0         | 100   |
| Built Up            | 482               | 0                | 177       | 119          | 16492    | 17270     | 95.5  |
| Column Total        | 22495             | 1621             | 19745     | 37257        | 17997    | 99115     |       |

Overall accuracy for 2010 classified image is 94.63%

Table 4
Contingency Matrix of classified image, 2017.

| Data                | Built up | Bare land | Dense vegetation | Water bodies | Sparse vegetation | Row total | %     |
|---------------------|----------|-----------|------------------|--------------|-------------------|-----------|-------|
| Built up            | 84390    | 260       | 428              | 958          | 829               | 86865     | 97.16 |
| Bare Land           | 565      | 61086     | 240              | 73           | 920               | 62253     | 98.13 |
| Dense Vegetation    | 87       | 2         | 51335            | 673          | 133               | 52230     | 98.29 |
| Water Bodies        | 0        | 0         | 0                | 0            | 0                 | 146025    | 100   |
| Sparse Vegetation   | 81       | 274       | 4990             | 27           | 61988             | 67360     | 92.02 |
| Column Total        | 85123    | 61622     | 56993            | 147693       | 63002             | 414733    |       |

Overall accuracy for 2017 classified image is 97.1%

Table 5
Change detection Matrix in hectare (2002–2010).

| LULC Class | Built Up | Water bodies | Bare land | Dense vegetation | Sparse vegetation | Total     |
|------------|----------|--------------|-----------|------------------|-------------------|-----------|
| Built Up   | 1600.178 | 0.292        | 1186.065  | 1.103            | 92.272            | 2879.91   |
| Water Bodies | 0.068     | 7983.179     | 140.963   | 3.487            | 133.628           | 8249.94   |
| Bare Land  | 296.55   | 30.6         | 71508.848 | 842.04           | 911.655           | 73589.693 |
| Dense Vegetation | 8.64     | 5.67         | 1537.492  | 2186.325         | 909.112           | 4647.239  |
| Sparse Vegetation | 128.903 | 20.836       | 5936.153  | 559.372          | 3911.445          | 10556.709 |
| Total      | 2034.337 | 8040.577     | 80409.488 | 3592.755         | 5968.125          | 41567.915 |

Table 6
Change detection Matrix in hectare (2010–2017).

| LULC Class | Built Up | Water bodies | Bare land | Dense vegetation | Sparse vegetation | Total     |
|------------|----------|--------------|-----------|------------------|-------------------|-----------|
| Built Up   | 2676.983 | 4.005        | 2142.81   | 23.49            | 394.267           | 5241.555  |
| Water Bodies | 0.675     | 8046.922     | 32.828    | 5.872            | 28.508            | 8114.805  |
| Bare Land  | 121.5    | 51.188       | 64772.527 | 633.622          | 4156.448          | 69735.285 |
| Dense Vegetation | 5.197   | 35.932       | 1823.872  | 2260.057         | 739.372           | 4864.43   |
| Sparse Vegetation | 75.555 | 109.665      | 4817.655  | 1724.198         | 5238.113          | 11965.186 |
| Total      | 2879.91  | 8249.94      | 73623.78  | 4651.74          | 10565.37          | 10565.37  |

Acknowledgments

Our hearty thanks to the Editor-in-Chief and anonymous reviewer for his valuable suggestions to improve in the present form.

Transparency document

Transparency document associated with this article can be found in the online version at https://doi.org/10.1016/j.dib.2019.103880.
References

[1] Tamam Emiru, Hasan Raja Naqvi, Mohammed Abdul Athick, Anthropogenic impact on land use land cover: influence on weather and vegetation in Bambasi Wereda, Ethiopia, Spatial Inf. Res. 26 (4) (2018) 427–436. https://doi.org/10.1007/s41324-018-0186-y.

[2] Messay Mulugeta, Bechaye T, Addis Ayano, Data on spatiotemporal land use land cover changes in peri-urban addis ababa, Ethiopia: empirical evidences from koye-fecheand qilinto peri-urban areas, Data in Brief 12 (2017) 380–385.

[3] Tarekegn Girma, Tebarek Lika, Molla Maru, Data on spatiotemporal land use land cover changes in peri-urban West Arsi Zone, Ethiopia: empirical evidences from Shashemene peri-urban areas, Data in Brief 18 (2018) 747–752.

[4] Chaltu Taffa, Teferi Mekonen, Messay Mulugeta, Bechaye Tesfaye, Data on spatiotemporal urban sprawl of dire dawa city, eastern Ethiopia, Data in Brief 12 (2017) 341–345.

[5] Sizah Mwalusepo, Eliud Muli, Asha Faki, Suresh Raina, Land use and land cover data changes in Indian ocean islands: case study of unguja in zanzibar island, Data in Brief 11 (2017) 117–121.

[6] Robert Pazúr, Janine Bolliger, Enhanced land use datasets and future scenarios of land change for Slovakia, Data in Brief 18 (2018) 747–752.

[7] M. Mohan, S.K. Pathan, K. Narendrareddy, A. Kandya, S. Pandey, Dynamics of urbanization and its impact on land use land cover: a case study of Mega city Delhi, J. Environ. Prot. 2 (2011) 1274–1283.

[8] M. Thompson, Standard land cover classification scheme for remote sensing application in South Africa, South Afr. J. Sci. 92 (1996) 34–42.

[9] R. Manandhar, I.O.A. Odeh, T. Ancev, Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement, Rem. Sens. 1 (2009) 330–344.

[10] A.S. Mohammed, A.A. H.R. Naqvi, Z. Firdouse, An assessment and identification of avalanche hazard sites in Uri sector and its surroundings on Himalayan mountain, J. Mt. Sci. 12 (6) (2015). https://doi.org/10.1007/s11629-014-3274-z.