Detecting Land Use and Land Cover and Land Surface Temperature Change in Lilongwe City, Malawi

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Abstract

In southeast Africa, Lilongwe city had an observed rapid population growth over the past decade and a half. The same city also had recently observed increased temperatures and adverse weather conditions such as occasional heavy storms which caused severe flooding in January 2017 and December 2017. It was therefore thought wise to do a land use and land cover (LULC) study of the city over time to detect land cover changes and its effect on land surface temperatures (LST). Landsat imagery was acquired for the year(s) 2008, 2013 and 2017 and it was classified to detect LULC changes for these given years. A significant (P<0.05) expansion of the city was detected especially between 2008 and 2013. The LST was derived from modelling NDVIS, from which emissivity was calculated and then the LST was estimated. There was an inverse regression (r²=0.65) with a high correlation (r=0.806) between NDVI and LST. With urbanization, the natural and agricultural land was converted into settlements resulting in lower NDVIS and higher land surface temperatures. It was concluded that urbanization, amongst others can therefore definitely contribute to global warming.

Keywords: Malawi, land cover, land use, emissivity, normalized vegetation index, land surface temperature

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INTRODUCTION

Population growth is at the centre of sustainable development and will be influential in the realization of the 2030 agenda for sustainable development [1]. The world population is projected to reach 9.8 billion in 2050 and more than half of the anticipated growth in global population between now and 2050 are expected to occur in Africa [1]. The food resources and land available to produce food, shrinks with this rapid average increase in global population. Along with global population increase, urbanization also takes place at a large scale, exerting pressure on the natural resources.

According to 2014 reports, over half of the world’s population (54%) lives in urban areas with some variability of urbanization amongst countries [2]. It was also found that urbanization takes place at a faster pace in the world’s middle and low income countries [2]. The majority of African countries fall in the middle income category with rapid generally observed rates of urbanization and population growth. Lilongwe city, Malawi’s capital city in east Africa, is one example of the latter.

There are casual observed patterns of urbanization in townships in Lilongwe city and district which is increasing and there has been a major change in settlement patterns for the past 15 years. In addition, the drainage system in the city has also been affected by the rampant urbanization, causing occasional flooding of the townships/suburbs. However, the effect of urbanization on land surface temperature change has not been well investigated in the district. This study is therefore aimed at applying tools of Geographic Information Systems (GIS) and Remote Sensing to achieve the following objectives:
Detecting LULC and LST Change in Lilongwe City

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To determine the extent of land use and land cover change in the city over time;

To find the relationship between land use and land cover change and land surface temperature change.

Landsat data sets were used for the year(s) 2008, 2013 and 2017 to determine changes in LULC and LST. Urbanization in Lilongwe city was observed to be rapid during this time period.

GEOGRAPHY, CLIMATE AND DEMOGRAPHY OF STUDY AREA

Malawi is located in south east Africa between latitudes 9°22' and 17°08'S and longitudes 32°40' and 35°55'E with a current population of 18.6 million and an annual average growth rate of close to 3%. The country is approximately 860 km in length from north to south and 250 km wide at its broadest point (Figure 1) [3]. Malawi’s capital city, Lilongwe, falls in Lilongwe district which is located in the plains of the Central Region which are between 1,200 and 1,400 m above sea level [4]. Apart from the city and other urban towns, Lilongwe district is covered by forest reserves and land under agricultural cultivation (Figure 2). The city has an area of 456 km² and its population has been growing from 440,471 to 661,021 according to 1998 and 2008 census respectively while the current population is 1,170,711 according to the 2015–16 Malawi demographic and health survey report [5].
Malawi has a sub-tropical climate and experiences two seasons. A cold season (winter) which is cool and dry is experienced from May to August with mean temperatures between 4 and 10°C with no or little precipitation. On the other hand, a hot season (summer) is grouped into a hot dry season which stretches from September to October with average temperatures ranging from 25 to 37°C and a hot wet season which spans from November to April. The warm wet season is characterized by precipitation with average rainfall varying from 725 to 2,500 mm with Lilongwe having an average of 900 mm of rainfall [6].

DATA AND METHODOLOGY
Multi-temporal data acquired from LandsatETM+ (2008), LandsatETM+ (2013) and LandsatOLI (2017) satellite imagery from USGS (www.earthexplorer.usgs.gov) data sets were used for the basis of this study and a brief description of the data used is given in Table 1. The first step was to acquire the data sets for the study area and period; then a geometric and radiometric correction was done. Images for the study period were classified and the resulting land use and land cover change was observed and analyzed. Normalized Difference Vegetation Index (NDVI) obtained from input prepossessed satellite imagery was used to estimate emissivity of different (bio) physical features on ground and hence a land surface temperature algorithm was used to estimate LST. Figure 3 illustrates the broad activities performed to produce the land surface temperature and land use, land cover output.

Fig. 2: The Location of the Study Area within Lilongwe District in Malawi, South East Africa (Projection: WGS 84/UTM Zone 36S).
Table 1: A Brief Description of Data Used in the Study.

<table>
<thead>
<tr>
<th>Satellite Data</th>
<th>Production Date</th>
<th>Spatial Resolution (m)</th>
<th>Source</th>
</tr>
</thead>
</table>

Land Use Land Cover Classification
Quantum GIS 2.1.4 Essen was used for the entire process used to come up with the project outputs (Figure 3). The data sets were pre-processed using the semi-automatic classification plug in. Composite images were then created from a selection of visible bands from the acquired respective Landsat data sets to aid the process of classification. The composite images were then first clipped to the extent of the study area before classification was done. Classification was then done and grouped in the following four major classes: Settlement, Vegetation, Bare soil and Water (Figure 4). Ten training sites per class were used to perform a supervised classification of the major classes. Maximum likelihood algorithm was used for the final classification output. Filtering was done to remove isolated pixels in the final classification output.

Land Surface Temperature Estimation
In order to achieve a land surface temperature map output, NDVI and emissivity raster calculations were performed. NDVI provides a standard method of comparing vegetation greenness between satellite images and the index values range from -1 to +1 with high values indicating a health vegetative cover while negative values indicate a land surface with very little or no vegetative cover [7, 8].

Emissivity is the ratio of energy emitted from a natural material to that from an ideal blackbody at the same temperature. A study by Griend and Owe showed that thermal emissivity highly correlated with NDVI after a logarithmic transformation with a correlation coefficient of R=0.94 [9]; hence NDVI values indicating the density of vegetation can be used for estimating emissivity. The following model was used to calculate NDVI using the following bands:
NDVI=(NIR–R)/(NIR+R)
Thus, NIR (Band 4) and R (Band 3) for Landsat 5 and Landsat 7 respectively, while Bands 5 and 4 are used for Landsat 8 [10].

Before calculating land surface temperature, the following conditions were set and emissivity was then calculated from the NDVI using the algorithm [9]:
If: NDVI<0.185 then assign 0.995;
NDVI>=0.185 and <0.157 then assign 0.970;
NDVI>=0.157 and <=0.727 then assign the formula 1.0094+0.047×ln(NDVI);
NDVI>0.727 then assign 0.990.

The NDVI values for the study area were ranging from 0.157 to 0.727 and therefore the following linear equation was used to calculate emissivity:
Emissivity =1.0094+0.047×ln (NDVI).

During LST calculation, image pre-processing with Quantum GIS converts digital numbers of the thermal bands (Band 6) and (Band 10) for Landsat 5 or 7 and Landsat 8 respectively of the satellite imagery to spectral radiance using bias and gain value and satellite brightness temperature is converted from degrees Kelvin to estimated land surface temperature in degrees Celsius by subtracting 273.15. The land surface temperatures for the study period could then be calculated, using the following algorithm with values of wavelength of emitted radiance ($\lambda$)=10.8 $\mu$m for Landsat 7 thermal band (Band 6) and ($\lambda$)=11.45 $\mu$m for Landsat 8 thermal band (Band 10) [11]:

$T=T_B/[1+(\lambda \times T_B/c_2) \times \ln (e)]$

Where,
$T= $ Land Surface Temperature (LST),
$T_B= $ Thermal band,
$e= $ emissivity,
$\lambda= $ wavelength of emitted radiance,
$c_2= $ Planck’s constant $=6.626 \times 10^{-34}$ Js,
$s= $ Boltzmann constant $=1.38 \times 10^{-23}$ J/K, and
$c= $ velocity of light $=2.998 \times 10^8$ m/s.
RESULTS AND DISCUSSION

Land Use and Land Cover Changes

Significant land use land cover changes could be observed on the study area for the years, 2008, 2013 and 2017. The land cover changes clearly depict the increase in settlements in the area as a result of urbanization at the expense of natural vegetation and agriculture land. The settlements in 2008 only covered 35% of the study land surface area. The settlements increased to 80 and 83% in the 2013 and 2017 years respectively (Figure 5a–c). Table 2 shows a summary of LULC over the study area for the specified period.

Land Surface Temperature Changes

The NDVI changes on the study area are crucial for the production of land surface temperature maps. Variation in NDVI also gives a good indication of topography, slope, solar radiation and other factors and not only on vegetation density and amount [12]. Since NDVI is a common measure of land surface

Table 2: Land Use Land Cover (LULC) Distribution.

<table>
<thead>
<tr>
<th>Macro Class</th>
<th>2008: Area (%)</th>
<th>2013: Area (%)</th>
<th>2017: Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Settlement</td>
<td>35.282</td>
<td>80.6</td>
<td>82.801</td>
</tr>
<tr>
<td>Vegetation</td>
<td>15.159</td>
<td>5.4</td>
<td>4.585</td>
</tr>
<tr>
<td>Bare Soil</td>
<td>49.439</td>
<td>13.8</td>
<td>12.599</td>
</tr>
<tr>
<td>Water</td>
<td>0.119</td>
<td>0.017</td>
<td>0.013</td>
</tr>
</tbody>
</table>

Fig. 4: Land Use Land Cover Changes for 2008, 2013 and 2017.

Fig. 5: (a) LULC for 2008; (b) LULC for 2013; (c) LULC for 2017.
greenness, the assumption is that this NDVI would be positively correlated to the amount of the actively growing vegetation in the image pixel area. With higher NDVIs, higher plant biomass cover is expected and therefore resulting in lower land surface temperatures. Changes in NDVI between 2008 and 2013 were related to land cover changes. Thus as the area under settlements increases, there was a gradual decline in NDVI values (Figure 6).

Fig. 6: Changes in NDVI for 2008, 2013 and 2017.
Changing cropping patterns of agricultural land are the principal regulating factors behind such dynamism of NDVI. Most of the land surface change took place in the northern part of the city (Figures 7 and 8) although there is little change in the NDVI maps (Figure 6). This can be explained by the fact that most of the land in the northern part of the city was converted from bare soil to settlements and therefore indicates insignificant changes in NDVI values, but had significant increases in land surface temperatures for the subsequent years of study (Figure 6). Spatial distribution of land surface temperature in Lilongwe city ranged from 22 to 29°C.

Fig. 7: Changes in Land Surface Temperatures for 2008, 2013 and 2017.
It was found that there was an inverse regression ($r^2=0.65$) with a high correlation ($r=0.806$) between the NDVI and the land surface temperatures on the study area (Figure 9). Swades and Zaiul also found a similar relationship in West Bengal, India [13].

CONCLUSION

There are many other factors contributing to increases in land surface temperatures. Land cover change in the form of urbanization is a contributing factor ($r=0.806$) to an increase in land surface temperature. It is very important to study such trends of land surface temperature change because the changes have a direct impact on local weather pattern, for example, rate of precipitation. In addition, such rise in LST affects general human health and welfare, agriculture and food production and leads to an increase in energy demand.

REFERENCES


Cite this Article