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# Dynamism of Land use Changes on Surface Temperature in Kenya: A Case Study of Nairobi City

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**Abstract:** Land surface temperature (LST) forms an important climate variable related to climate change and is an indicator of the energy balance at the surface since it's a key parameter in the physics of the land surface processes. The main aim of the study is to examine the dynamic effects of land use changes on land surface temperature through analysis of the relationship of LST, NDVI and LULC for a period of 24 years. The study area is Nairobi between 36°4' and 37°10'. Landsat satellite images of 1986, 1995, 2002 and 2010 was used to derive land use land cover (LULC), normalized difference vegetation index (NDVI) and LST. It was found out that urbanization was taking place with forest, plantations, shrubs, grassland and bare land changing to built-up. It was also clear that there exist a negative correlation between NDVI and LST hence indicating a reduction in vegetation cover to bare land or built-up would lead to increase in land surface temperature (LST).

**Keywords:** Landuse, Landcover, Land Surface Temperature, Normalized Difference Vegetation Index, Thematic Mapper, Enhanced Thematic Mapper

## 1. Introduction

Global warming is increasing as a result of massive changes in land use land cover more so due to urbanization which leads deforestation and reduction in agricultural areas. Most urban areas have higher temperatures as compared to the country side according to the greenhouse effect derived from carbon effluent machinery and use. With different land use types having different land surface temperature indicate that it can be used to show LST trends [1].

With ground-based observations reflecting only thermal condition around the station, it's somewhat difficult to estimate LST with expected precision hence in recent times thermal remote sensing has been used to assess the LST. Satellite Images are widely used to track changes in LULC due to their spectral, temporal and spatial characteristics. The thermal band widely used to estimate the thermal condition of land surface is less utilized due to its low resolution. Surface temperature can be estimated on daily basis using thermal bands of NOAA/AVHRR, GEOS, MTSAT. However, this kind of data has a low resolution of around 1-5 km spatial resolution making it suitable for climate studies at a more regional level. This poses a challenge in recognition of different land cover types within a single pixel. The Landsat TM and ETM+ with 60m spatial resolution of thermal infrared band enable users to define the more detailed surface temperature.

Land use land cover changes alters the sensible and latent heat fluxes that exist within and between the earth's surface and boundary layers thus influencing land surface-atmosphere interactions [2]. The changes in LULC affects land surface properties where LST is one of the properties and is assessable continuously using satellite imagery.

The NDVI refers to a dimensionless variable and its index provides information on vegetation vigor situation [3]. This means it can be used as an indicator of climate change since it assesses vegetation which is a major component of land cover. This research aims to examine the dynamic effects of land use changes on surface temperature through analysis of the LST, NDVI and LULC using Landsat TM and ETM for a period of 24 years.

## 2. Study Area

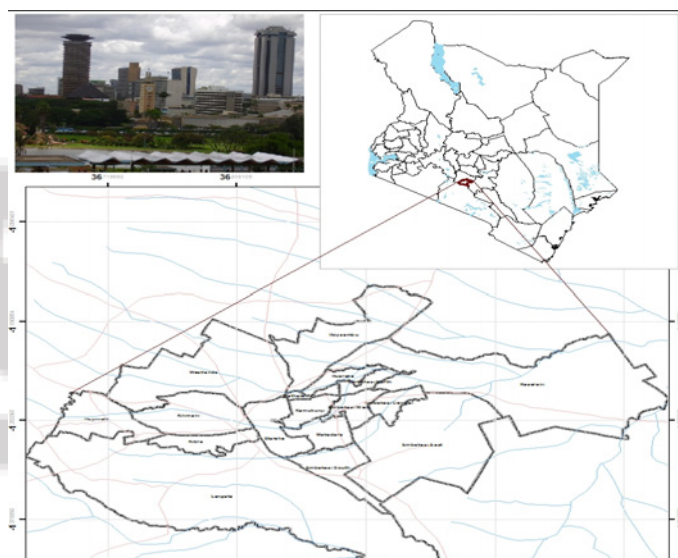


Figure 1: Map of the study area

The study area, Nairobi County, extends between 36° 4' and 37° 10' E and approximately between 1° 9' and 1° 28' S, covering an area of 689 km<sup>2</sup>. The average altitude is approximately 1700m above sea-level with a mean annual rainfall of about 900 mm. Nairobi County has vegetation

varying from grassland scattered with acacia trees in the east with some hardwood forests in the higher areas to the west. The General Land use within the study area varies from Urban-built, agriculture, rangeland and forests. Nairobi has recorded urban explosion in recent years with conversions of pervious surfaces to impervious surfaces. Nairobi County has a population of about three million, with population densities varying widely within the county.

### 3. Data and Methodology

The following procedure was carried out to derive the NDVI and surface temperature.

#### 3.1 Conversion of the Digital Number (DN) to Spectral Radiance ( $L_\lambda$ )

The spectral radiance ( $L_\lambda$ ) is calculated using the following equation [4]

$$L_\lambda = LMIN_\lambda + \left( \frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX} \right) QCAL \quad (1)$$

Where,

- QCALMIN = 1, QCALMAX = 255 and QCAL = Digital Number.

- The LMIN $_\lambda$  and LMAX $_\lambda$  are the spectral radiances for band 6 at digital numbers 1 and 255 respectively

$$\rho_\lambda = \frac{\pi \cdot L_\lambda \cdot d^2}{ESUN_\lambda \cdot \cos \theta_s} \quad (2)$$

Where:  $L_\lambda$  is the spectral radiance,  $d$  is the Earth-Sun distance in astronomical units,  $\theta_s$  is the solar zenith angle in degrees. ESUN $_\lambda$  is the mean solar exoatmospheric irradiance. ESUN $_\lambda$  values from the *Landsat 7 Science Data Users Handbook* for Landsat 7 ETM+. ESUN $_\lambda$  [5]. The above computation ensured accurate values for the inputs and outputs.

#### 3.2 Land use land cover retrieval

The land use and land cover classification system used in this report conforms to the classification process level I as outlined by [9]. A total of five land use land cover classes were derived namely; built-up, Agricultural/forest, shrubs/grassland, water and bare land. Landsat data was used to carrying out classification using the maximum likelihood algorithm and supervised classification for all the years under study to obtain land use land cover classes. Various types of classes were identified using false colors of the different band combination which enhanced features and improved on the interpretations. Accuracy assessment was done by randomly selecting points in which the two high resolution images were used to check against the classified images for all the images and the accuracy assessment results produced.

#### 3.3 Normalized Difference Vegetation Index retrieval

$$NDVI = \frac{NIR - R}{NIR + R} \quad (3)$$

Where: NIR is the near infrared band 4, R is the red band 3[3]

#### 3.4 Land Surface Temperature Retrieval

The brightness values obtained was then converted into land surface temperature. Since brightness temperature from equation 4 refers to black body with emissivity  $\varepsilon$  equal 1, the temperature of real surface would be different.

##### 3.4.1 Brightness Temperature Retrieval

The ETM+ thermal band data can be converted from spectral radiance temperature, which assumes surface emissivity = 1 [4]

$$BT = K2 / \ln(K1 / L_\lambda + 1) \quad (4)$$

Where,

- T = Effective at-satellite temperature in Kelvin
- K1 = Calibration constant 1 (watts/meter squared\*ster\* $\mu$ m) (666.09)
- K2 = Calibration 2 (Kelvin) (1282.71)
- $L_\lambda$  = Spectral radiance (watts/meter squared\*ster\* $\mu$ m)

##### 3.4.2 Emissivity Retrieval

In this study the method of emissivity estimation from the NDVI by [7] and [8] has been applied.

$$\varepsilon = \begin{cases} 0.979 - 0.035 \rho_R & NDVI < 0.2 \\ 0.986 + 0.004 P_V & 0.2 \leq NDVI \leq 0.5 \\ 0.99 & NDVI > 0.5 \end{cases} \quad (5)$$

Under this method pixels were divided into three groups according to the NDVI value. If NDVI exceeds 0,5 then pixel is assumed to be entirely covered by vegetation. Under such cases the  $\varepsilon$  equal 0.99 were assigned to them. For the pixels where NDVI ranges from 0.2 to 0.5 the Fractional Vegetation Cover ( $P_V$ ) was calculated using the below equation 6.

$$P_V = \left( \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \right)^2 \quad (6)$$

Where  $NDVI_s = 0.2$  which is value for pure soil pixel and  $NDVI_v = 0.5$  which is value for pure vegetation pixel.

Finally the  $\varepsilon$  was obtained from simple linear regression using  $P_V$  values using above equation 6. Where pixels had NDVI values lower than 0.2 the  $\varepsilon$  is calculated from reflectance in red band. If the emissivity is known the LST could be determined from simple formula [6]

$$LST = \frac{BT}{\varepsilon^{0.25}} \quad (7)$$

Both  $BT$  and  $LST$  are expressed in Kelvins. Most of the emissivity estimation is based on Normalized Difference Vegetation Index (NDVI) from equation 3.

### 4. Results and Analysis

The land use land cover maps derived from the multispectral Landsat data using the maximum likelihood classification method for the years 1986,1995,2002 and 2010 images are as shown below in figure 2.

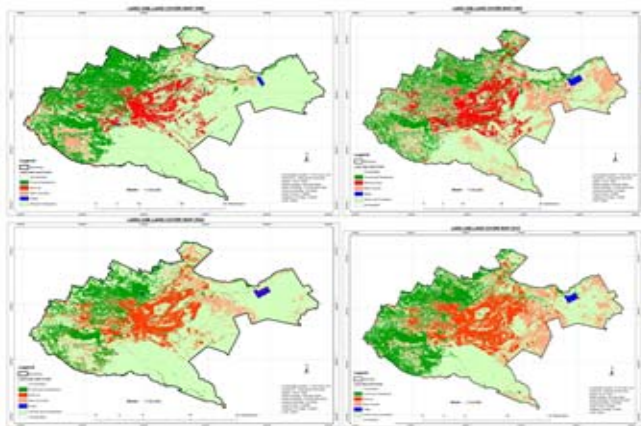


Figure 2: Land use land cover maps

From the above maps it seen that the built up has increased of the years being a clear indication of urbanization. Forest/plantations, shrubs and grassland have significantly reduced over the time hence increasing the amount of latent heat flux from the surface to the atmosphere. Visual interpretation indicates increase in bare land.

LST was generated for the years 1986, 1995, 2002 and 2010 for the study area as shown below in Figure 3.

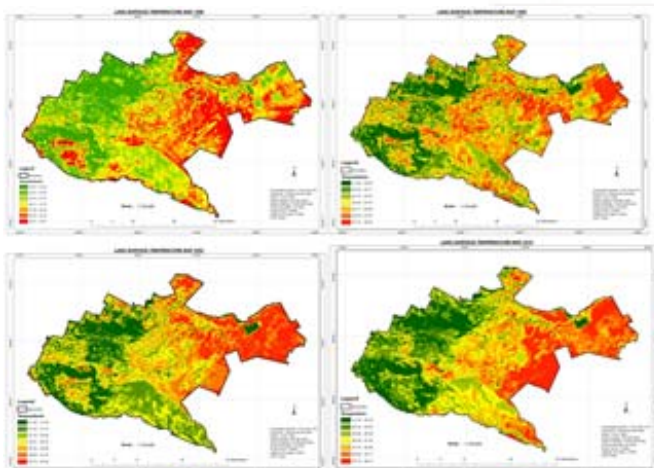


Figure 3: LST maps

From the visual interpretation of the above maps, it's clear that an area covered by green vegetation contains the lowest temperature and built-up and bare land having the highest temperature. To show a spatial distribution of the surface radiant temperature, LST map was classified as shown above into 7 classes based on a classification scheme using the standard deviation. The averaged LST in the classes was regarded as LST in Nairobi hence depicting spatial distribution

#### 4.1 Correlating LULC and LST

The relationship between LST and LULC has shown a positive correlation between Built-up and bare grounds. A cross comparison between the LST and LULC map indicated a minimum of about 20° in water bodies and a maximum of 34°-36° in bare grounds and built-up areas. Areas of moderate vegetation had moderate temperatures. The

temporal distribution can be explained using the figure 4 below. Generally the figure indicates a general and steady increase in LST for bare grounds and built-up. Vegetated areas have a negative correlation hence having very low temperatures. Areas occupied by water too had low temperatures.

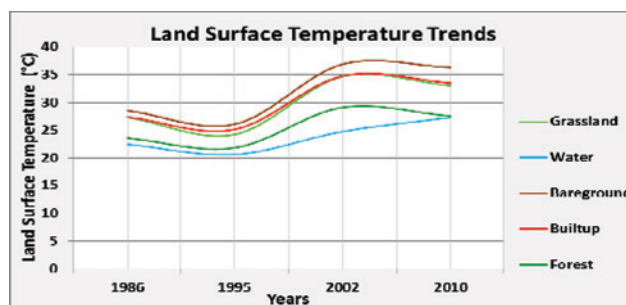


Figure 4: LST Trends

NDVI was generated for the study period as shown in figure 5 below.

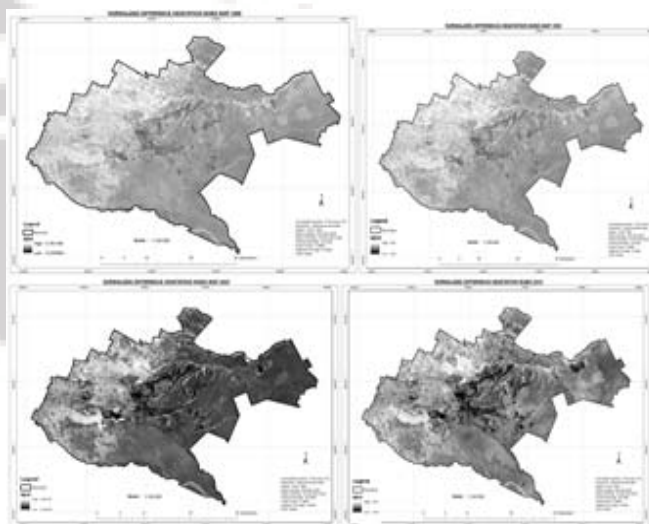


Figure 5: NDVI maps

To examine the spatial distribution of the NDVI, NDVI maps were produced for the entire study period and a classification assigned to denote the distribution. In the study, NDVI was calculated to provide estimates of the abundance of actively photosynthesizing vegetation. Large NDVI denoted large fraction of vegetation per pixel.

#### 4.2 Correlating NDVI and LST

Lower LST was found in areas of high vegetation cover since the amount of vegetation determines the LST by latent heat flux from the atmosphere via evapotranspiration. The correlation between NDVI and LST has shown to be valuable for studies of urban climates [10]. For this study, the use of NDVI was to examine the relationship between the vegetation cover and LST.

The temporal distribution of the NDVI can best be explained from the below figure 6. Vegetated areas were found to have the highest NDVI values as compared to built-up and bare

grounds that had the lowest values.

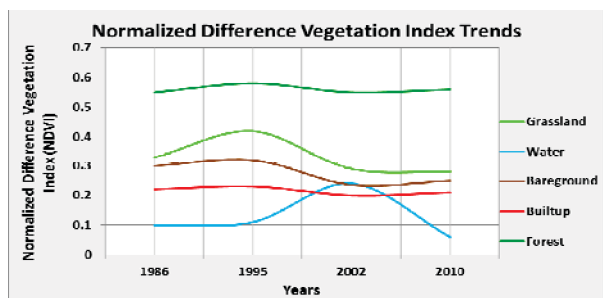


Figure 6: NDVI Trends

## 5. Discussion and Conclusion

From the research results, it's confirmed that a negative correlation between LST and NDVI as already deduced from other studies. It was also found out that LST was very sensitive to moisture content in the atmosphere as well as vegetation cover. LST was very closely linked to built-up and bare grounds for the case of LULC.

Areas of high LST were identified as the built-up, i.e. the central business districts, industrial areas and the informal settlements and bare grounds mostly around the quarry's. The results also suggest a high correlation between LST and LULC hence revealing different environmental impact factors attributed by urbanization process in Nairobi. Increase in urbanization process leads to replacement of natural surfaces and a continuous increase in artificial LULC in form of roads, buildings and other anthropogenic surfaces making it impervious [11]. The continuous and enormous changes of the LULC with urban sprawl and encroachment and destruction of the ecosystem in our urban green space has led to the increase in LST intensity.

With the world's population estimated to live in urban areas said to increase significantly over the coming years, and with the highest growth said to happen in developing world, its imperative the problem in urban areas will be the increase in surface temperature as a result of continuous alteration and conversion of previously pervious surfaces to impervious surfaces. The changes will cause environmental impacts with air pollution a factor that contributes to global warming increasing the surface temperature. Others affect the absorption of solar radiation, evaporation rates, surface temperature, the storage of heat and wind turbulence all conditions fit to contribute to the urban heat island phenomenon [12].

Based on the current rate of urbanization coupled with ever increasing population growth, it's assumed that the urban built-up areas may continue to increase further with the same projection as the past; hence further increase in LST values around the urban areas can be predicted. This is based on increase in population and anthropogenic materials.

With the research study results indicating a positive correlation between LST and LULC, it can be concluded that an increase in LULC would mean an increase in LST too.

This indicates the importance of the research findings to planners, urban managers and decision makers and of particular importance to the county government of Nairobi to take up actions and draft of policies to further control the LULC changes so as to minimize and reduce their impacts hence mitigating the urban micro-climates. It's recommended for action to be taken to introduce green building as well as adopt measures that would ensure continuous preservation of Nairobi green corridors and space.

## 6. Acknowledgement

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