



A Retrieval of Spatial-Temporal Surface Albedo from Landsat-8 Surface Reflectance and its Relationship with Land Surface Temperature

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Abstract

The surface energy budget is controlled by surface albedo, and the climate and environment are significantly impacted by albedo-induced radiative forcing. The algorithms and outcomes of surface albedo have been detailed in previous reviews. In this investigation, three satellite photos that had less than 10% land and scene cloud coverage were taken from the official website of the US Geological Survey (USGS). The satellite images used in this investigation were from the years 2013, 2017, and 2022. Using the conversion of digital numbers into thermal spectral radiance and subsequently to brightness temperature using the Planck radiation function, the land surface temperatures (LST) were retrieved from Landsat 8 data. Without adjusting for air conditions, albedo was calculated by linearly combining the reflectance of the OLI-Landsat 8 bands. With a Pearson's r value of -0.78473, findings indicated a negative correlation between albedo and LST in 2013. Albedo and LST had a greater inverse association in 2017 and 2022, with Pearson's r equal to -0.92604 and -0.88849, respectively. By increasing surface albedo, the study shows specific metropolitan areas to create UHI mitigation strategies. Satellites offer a useful tool for tracking the effects of the albedo urban pattern on cooling or heating.

Keywords: surface albedo; radiative forcing; urban; Landsat 8; land surface temperature.

INTRODUCTION

The amount of solar radiation reflected by the surface is commonly managed by land surface albedo, which in turn manages the Earth's energy budget (Liang *et al.*, 2010). An albedo is a number that quantitatively defines the absorption/reflection behaviour of a surface. It is the total hemispherical reflectance of a particular surface integrated over the solar spectrum, including specular and diffuse reflection. Albedo levels typically range from 0.10 to 0.50, with metallic surfaces having greater values. The past three decades have seen steady advancements in satellite remote sensing of land surface albedo, and several satellite products are now available for use in applications requiring coarse-resolution climate modelling (He *et al.*, 2014a; Liang *et al.*, 2013; Muller *et al.*, 2012; Riihela *et al.*, 2013; Wang *et al.*, 2013). Although there is a great demand for satellite albedo products with a fine spatial resolution that show the regional variability of land surface albedo and the fluctuations in albedo due to small-scale changes in land cover (Roman *et al.*, 2013; Shuai *et al.*, 2014). However, there are no products with such long-term, worldwide coverage available today. For example, scale discrepancies between coarse-resolution data

and ground measurements have prevented a more accurate evaluation of current satellite data for research on climate modelling in the absence of fine-resolution data (Burakowski *et al.*, 2015). Due to the free availability of Landsat data, albedo data may be used in applications that require data at finer spatial resolutions, such as ecosystem functioning assessment and urban environmental assessment (Zhou *et al.*, 2012), agricultural monitoring (Gao *et al.*, 2014; Li and Fang, 2015), forestry management (Kuusinen *et al.*, 2014), and monitoring of agriculture (Gao *et al.*, 2014; Lagomasino *et al.*, 2015). It is difficult to apply such physically-based or semi-empirical methods to data from fine-resolution satellite sensors because of the inadequate angular samples from one sensor over a short period for collecting surface anisotropy caused by the lower return frequency (such as Landsat). Previous studies revealed that failure to remove the impacts of the surface bidirectional reflectance distribution function (BRDF) can lead to inaccuracies of up to 60% in fine-resolution data, which highlights the relevance of converting surface directional reflectance to albedo (e.g., Gao *et al.*, 2014). For research on the surface energy budget related to long-term climate change, there is a growing demand for accurate and trustworthy surface

albedo products (e.g., Ghimire *et al.*, 2014). All of the approaches for determining surface albedo from Landsat data need surface reflectance produced from a precise atmospheric correction. It is unlikely to obtain an accurate surface reflectance when the landscape lacks dark, thick vegetation or when the visible bands are saturated. Large urban surfaces like pavements and rooftops, for instance, are covered with materials like cement and bitumen. Buildings can be made of composite materials in addition to glass, steel, concrete, bricks, and wood. Other surfaces are covered with plants, grass, or water, as seen in gardens, parks, or open areas. One of the surface characteristics that connects urban climate to land use and the cover is albedo or the proportion of incoming solar radiation reflected by the surface. This is because both surface reflectivity and total hemisphere emissivity are material qualities involved in radiant heat exchanges. It is reasonable to suppose that the average albedo of present roofs does not exceed 0.25 and that, with targeted refurbishment or interventions, their albedo may be increased to around 0.55 to 0.65. (Silva *et al.*, 2005; Wang and Davison, 2007; Giongo *et al.*, 2010; Lopes *et al.*, 2013; Souza *et al.*, 2014).

Remote sensing images generated by spaceborne and airborne sensors may be very helpful to obtain a global perspective of the albedo distribution across an urban region and of the accompanying land surface temperature (LST) trend. The albedo-LST link has been traced in this study using several remote sensing instruments with various spatial resolutions. This study's main goal is to determine the relationship between land surface temperature and surface albedo using Landsat TOA reflectance data. Additionally, the outcomes may be utilised to look at the uncertainties in datasets with coarse resolution over varied landscapes. Retroreflective materials (RRMs), such as glazed facades, appear to be an efficient way to boost urban albedo and reduce human heat emissions in residential areas (Morini *et al.*, 2017). Additionally, there has been a lot of interest in roof albedo, and analytical findings indicate that the albedo varies depending on the materials (such as the membrane, asphalt shingle, roofing aggregate, and tile materials) (Levinson *et al.*, 2020). Additionally, pavement is a crucial component of urban areas, and road albedo changes depending on the kind of material used and how old it is (Chen *et al.*, 2019; Sen and Roesler, 2016). Understanding and limiting climate change depend heavily on surface albedo.

Many surface albedo datasets, including those for land degradation (Liu *et al.*, 2017), fast surface dynamics (Wang *et al.*, 2018), and catastrophic catastrophe events, including forest fires, have been used to study slow climate change (Potter *et al.*, 2020). Many management techniques have been used to reduce greenhouse effects, such as afforestation (Kirschbaum *et al.*, 2011) and the use of high-albedo materials for pavement and roofs in urban areas, as these variations in surface albedo has a significant impact on the carbon trade-off (Lintunen and Rautiainen, 2021, Akbari *et al.*, 2009). Urban development is a significant human activity that causes a significantly slower rise in surface albedo as canopy coverings give way to darker impermeable covers (like roofs and pavement) (Trlica *et al.*, 2017; Tang *et al.*, 2018). Urban roof evaluation demonstrates that high-albedo materials can successfully reduce Urban Heat Islands (UHI) (Susca 2012). Along with materials, the LCA of pavement albedo also has a variety of effects on the carbon budget, with cement concrete pavement reducing CO²-equivalent emissions by 9.2 per cent and hot mixed asphalt pavement increasing emissions by 19.1 per cent (Yu and Lu, 2021). The objective of this study is to examine the algorithmic principles behind the retrieval of albedo from Landsat 8 images in relation to the land surface temperature of the study area.

MATERIALS AND METHODS

Study Area

Ogbomoso is located between 4° 14' 28.2° and 4° 14' 56.9° North and 8° 06' 70° and 8° 06' 99° East of the Equator. It is a derived Savannah region and is situated 104 kilometres north of Ibadan, 58 km north of Osogbo, 57 km south of Ilorin, and 53 km north of Oyo (Ogunkan and Jelili, 2019). Ogbomoso's strong resistance led to the sheltering of more than 140 communities. The town's rapid expansion was further aided by the entrance of missionaries and the building of Ladoko Akintola University of Technology, established in 1991. According to Bowen (1957), the population expanded from 25,000 in 1885 to over 166,000 in 1991 and was expected to be at 299,535 in the 2006 census. Due to demographic fluctuations, Ogbomoso's built-up area has expanded. The town's built-up area rose from 2 km² in 1935 to 4.5 km² in 1963, and Opeloyeru (1983) estimated that it would reach 24.3 km² in 1995 (Popoola, 2007) in 2003, it increased to 27.5 km². (Abolade, 2004). The region's geology is composed of Precambrian rocks that are characteristic of Nigeria's basement

complex (Rahaman, 1976). It frequently includes assemblages of rocks with lower metamorphic grades and notably higher proportions of mafic and ultramafic rocks (Ajayi and Adegoke, 1988). By nature, dendrites are the drainage kind. Locally, there are two different seasons in the Ogbomoso region: the rainy season, which normally lasts between March and October, and the dry season, which happens every year between November and February. The majority of Nigeria's southwest is affected by this tropical rain. The research region experiences an annual rainfall of 1016 to 1524 millimetres, with the majority of it occurring during the rainy season (Sunmonu *et al.*, 2013).

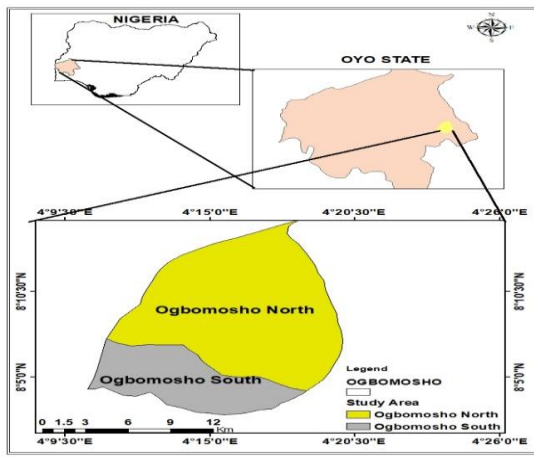


Figure 1: Map of Ogbomoso (inset: maps of Oyo state and Nigeria)

Dataset Preparation

Three satellite images with less than 10% land and scene cloud coverage, retrieved from the US Geological Survey's (USGS) official website (<http://earthexplorer.usgs.gov/>), were used in the study. The dataset utilised for this study consisted of satellite images from 2013, 2017, and 2022 (December, November, and January, respectively). The data months (dry season) were carefully chosen to prevent cloud cover issues and the influence of rainfall seasonality on the land surface temperature. Table 1 lists the satellite images that were used in the investigation.

Table 1. Satellite Specification

Satellite/ Sensor	Resolution	Path and Row	Date
Landsat 8 OLI	30m	191/054	18 th Dec. 2013
Landsat 8 OLI	30m	191/054	17 th Nov. 2017
Landsat 8 OLI	30m	191/054	27 th Jan. 2022

Land Surface Temperature (LST)

Landsat 8 OLI satellite images were used to determine the land surface temperature for the research region for the years 2013, 2017, and 2022. The three-year LST maps were then created, and over the research period, variations in LST were noted. LST estimation was done using Equations 1–5. (Tasumi *et al.*, 2008).

$$L_{\lambda} = A_{\lambda} + M_L * Q_{CAL}$$

(1)

Where: L_{λ} = TOA Spectral Radiance ($W / (m^2 \times sr \times \mu m)$); M_L = Radiance multiplicative scaling factor for the band; A_L = Radiance additive scaling factor for the band; Q_{CAL} = the quantized calibrated pixel value in Digital Numbers (DN)

The second stage included converting the TOA spectral radiance (L) measurements into another quantity known as the At-Satellite Brightness Temperature (TB)

$$TB = \frac{K_2}{\ln \frac{K_1}{L_{1+1}}}$$

(2)

Where: TB = At-Satellite Brightness Temperature, in Kelvin (K); K_1 , K_2 = Thermal conversion constants for the band

Equation 3 was used to translate the TOA Brightness Temperature into values for land surface temperature (LST).

$$LST = [TB / (1 + (\lambda * TB / \alpha)) * \ln \varepsilon]$$

(3)

Where: LST = Land Surface Temperature in Kelvin (K)

λ = the wavelength of emitted radiance

$\alpha = hc/k$ (1.438×10^{-2} mK)

h = Planck constant (6.626×10^{-34} J s-1), and

c = velocity of light (2.998×10^8 m s-1)

k = Boltzmann constant (1.38×10^{-23} J K-1)

ε = surface emissivity, calculated according to equation 4

$$\varepsilon = 0.004 * Pv + 0.986$$

(4)

Where: P_v is the vegetation proportion calculated with equation 5

$$P_v = \left[\frac{NDVI - NDVI_{min}}{NDVI - NDVI_{max}} \right]^2$$

(5)

273 was taken out of the basic numbers to get the land surface temperature readings in Celsius (°C) (K).

Vegetation Normalized Difference Index (NDVI)

The near-infrared and red spectral bands of Landsat's multispectral sensor are used to determine the NDVI. The idea behind measuring the NDVI is based on the highest radiation reflection in the near-infrared (NIR) spectral band and the absorption of light in the red (R) spectral band.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (6)$$

The range of the NDVI is from -1 to +1, with values close to -1 indicating a lack of vegetation and values near to +1 indicating a thick canopy.

Surface Albedo Retrieval

Using coefficients calculated from several linear regressions and the reflection bands of the satellite sensors. From images captured by Landsat 8 (OLI) in the years 2013, 2017, and 2022, the albedo of the study area was estimated. The reflectance of the bands (from 2 to 7) of the OLI-Landsat 8 was

combined linearly to determine albedo without atmospheric adjustment (toa.). (Equation 7):

$$\alpha_{toa} = p_2 \times r_2 + p_3 \times r_3 + p_4 \times r_4 + p_5 \times r_5 + p_6 \times r_6 + p_7 \times r_7 \quad (7)$$

Where: Chander and Markham (2003) derived the reflectance for each of the bands (from 2 to 7).

RESULTS AND DISCUSSION

Spatial distribution of Land surface temperature

The investigation of surface temperature revealed the temperature dispersion throughout the research region. In 2013, the research area's average LST was 30.86°C. In 2017, it rose to 34.37°C, and in 2022, it dropped to 28.16°C (Figure 2). Microclimatic variability may have had a strong influence on variation in LST. The coverage area with the lowest LST in 2013 was 2672.46 ha. In 2017, it expanded to 4362.57 ha, and in 2022, it slightly decreased to 3805.29 ha. In 2013, 8355.60ha of the land was covered by mild temperatures; in 2017, 8296.11 ha; and in 2022, 1521.45 ha. Very high temperatures were recorded throughout (Table 4). According to the geographical distribution data, Ogbomoso North LGA had a higher prevalence of high LST than Ogbomoso South LGA.

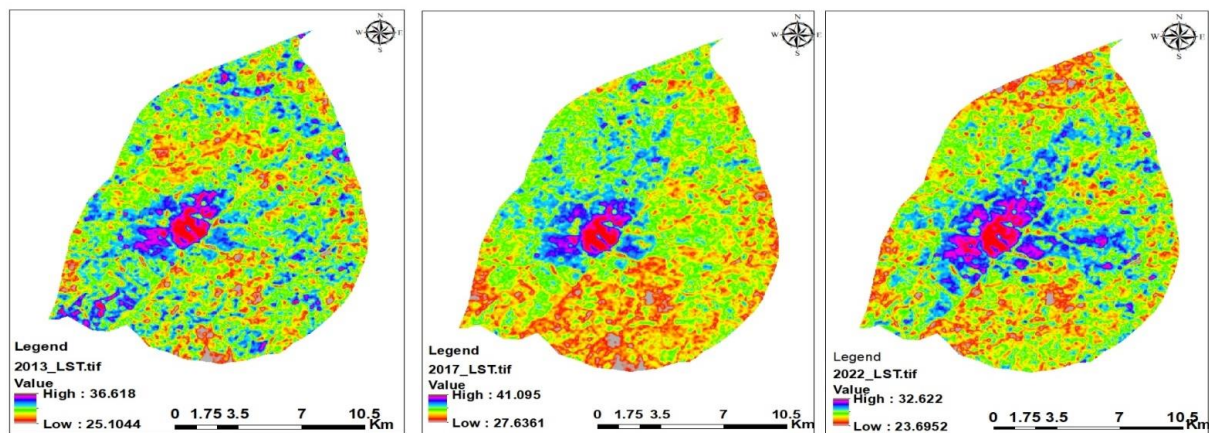


Figure 2: Land surface temperature maps of the study area in 2013, 2017 and 2022

Table 2: Observed spatial dynamics of LST in 2013, 2017 and 2022

Name	Area(ha)			Percentage (%)		
	2013	2017	2022	2013	2017	2022
Very Low	2672.46	4362.57	3805.29	10	16	14
Low	6565.68	8025.21	15024.24	26	30	56
Moderate	8355.60	8296.11	1521.45	30	31	6
High	6928.83	4891.14	3988.98	26	18	15
Very High	2260.44	1208.16	2443.23	8	5	9

Spatial distribution of surface albedo

In 2013, the research area's average albedo was 0.089, it rose to 0.114 in 2017, and by 2022, it had dropped to 0.085. (Figure 3). The region in 2013 with the greatest albedo was 1006.65 ha. It decreased to 613.89 ha in 2017 and increased to 1448.91 ha in 2022. In the years 2013, 2017, and

2022, it was high in areas covering 3757.05 ha, 2999.25 ha, and 4517.65 ha, respectively. In 2013, the study area's moderate albedo was 7117.56 ha. It reduced to 6304.14 ha in 2017 and 6063.75 ha in 2022. However, areas with the lowest albedo were 5885.46 ha, 7007.76 ha and 5962.22 ha in 2013, 2017 and 2022, respectively (Table 3).

Table 3: Spatial dynamics of Albedo in the years 2013, 2017 and 2022

Name	Area(ha)			Percentage (%)		
	2013	2017	2022	2013	2017	2022
Very Low	5885.46	7007.76	5962.22	22	26	22
Low	9016.47	9858.15	8789.67	33	37	33
Moderate	7117.56	6304.14	6063.75	27	23	23
High	3757.05	2999.25	4517.65	14	11	17
Very High	1006.65	613.89	1448.91	4	3	5

In 2013, 3.76% of the study area had very high albedo, though highly concentrated around the Kinnira area (Administrative Headquarters) of Ogbomosho North and the Arowomole area (Administrative Headquarters) of Ogbomosho

South. There were dotted ‘very high’ surface albedo across the study area. In 2017 and 2022, the highest surface albedo values were 2.29 and 5.41%, respectively.

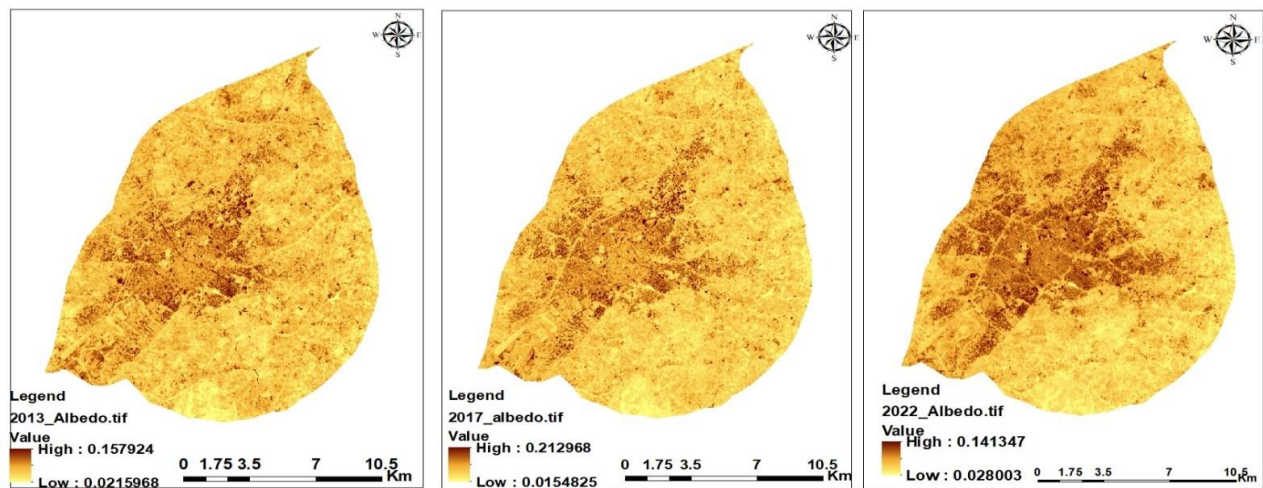


Figure 3: The spatial distribution of surface albedo in 2013, 2017 and 2022

Relationship between albedo and LST

There existed a negative association between albedo and LST in 2013 ($r = 0.78473$), which increased in 2017 ($r = -0.92604$) and 2022 ($r = -0.88849$) (Figures 4, 5 and 6). The hypothesis that high albedo levels imply lower LST values is supported by this association. Therefore, for the majority of pixels at 30 m, impervious percentage and canopy had the biggest effect in the simultaneous model, despite a few rare pixels with very high and extremely low albedo, showing a substantial influence on the modelled LST. These

results were consistent with earlier remote-sensing studies that stated that impermeable cover had a beneficial impact on urban LST, whereas canopy cover had a negative impact and albedo had a negligible impact (Kong *et al.*, 2014; Haashemi *et al.*, 2016; Jenerette *et al.*, 2016; Zhang *et al.*, 2016).

For both natural and manmade surfaces (such as buildings, roads, and paved surfaces), the dynamics in the spectral interactions between surface albedo (SA) and LST often shift as a result

of fluctuations in land cover type (Yoon *et al.*, 2019). Complex urban morphologies including block forms, plan density, facade density, building height, and layout orientation all contribute to the atmospheric interplay between urban surface albedo and LST (Groleau and Mestayer, 2013).

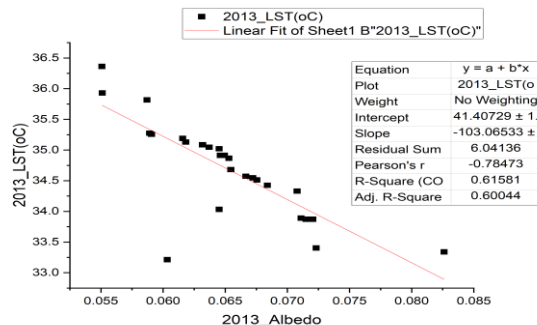


Figure 4. LST vs. Albedo scatterplot for the study area in 2013

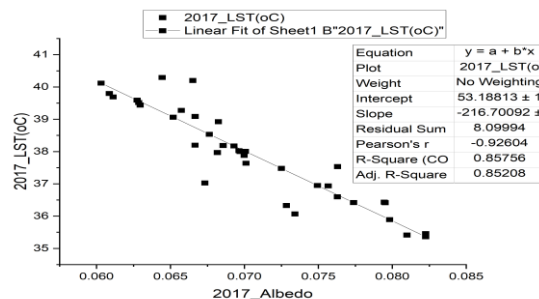


Figure 5. LST vs. Albedo scatterplot for the study area in 2017

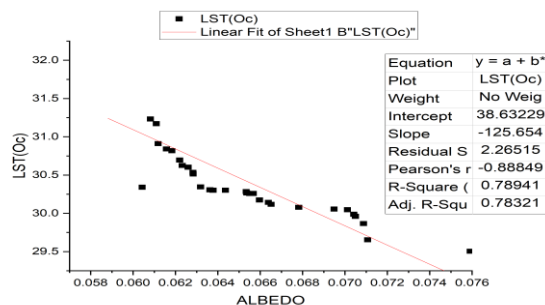


Figure 6: LST vs. Albedo scatterplot for the study area in 2022

CONCLUSION

Using data from Landsat 8, the study illustrates the existing "inverse" linear relationship between LST and albedo (OLI). The fluctuation and range of values of the LST and albedo relationship are confirmed by observing different years. Satellites are therefore an effective instrument for

monitoring the impact of the albedo urban pattern on cooling or heating.

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