An investigation of the relationship between surface albedo and urban cover types in a semi-arid region

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Abstract: Surface albedo, is a key parameter controlling the local energy budget, which in turn plays an important role in mitigating the effect of urban heat islands. This paper aimed to examine the relationship of surface albedo to major land cover categories, which include built-up areas, green covers, water bodies, and bare land. This study provides a new approach by using a 30 m spatial resolution of Landsat data over the study area, Baghdad, and relating surface albedo to the metrics of four biophysical parameters: Normalised Difference Vegetation Index (NDVI), Modified Normalised Difference Water Index (MNDWI), Normalised Difference Build-up Index (NDBI) and Normalised Difference Barren Index (NDBaI). A linear regression was generated to assess the correlation of surface albedo with these four biophysical parameters, and the results showed a strong positive correlation between surface albedo and both NDBI, and the NDBaI (r = 0.62 and r = 0.95, respectively), and a moderate correlation with NDVI (r = 0.4). There was also a strong negative correlation of surface albedo with MNDWI (r = −0.81).

Keywords: Baghdad; Biophysical parameters; NDVI; Semi-arid region; Surface albedo

1. Introduction

The term urban cover describes the main types of land use/land cover (LULC) surfaces in cities; these include built up areas, green cover, water, and bare land (1). In general, man-made surfaces offer a greater absorption of solar radiation (heat) and thus increase in temperature more than the vegetative surrounding areas (2, 3). This phenomenon leads to the well-known "urban heat island" effect. A number of studies have confirmed that dark surfaces such as asphalt and concrete in urban areas absorb the incident radiation during the day and release it at night (4, 5); other studies have pointed out that vegetation and water bodies have a cooling effect on the environment of urban areas (6).

Remote sensing is a significant tool in terms of studying, monitoring, and assessing the spatial variations of LULC categories and their effects on the urban climate and environment at a range of scales. Landsat data, including derived surface albedo and landscape indices, represent the best quality retrieval in terms of both spatial and temporal resolution, and these have thus been effectively employed in studying the characteristics of LULC categories, especially in the urban environments (7).
In this study, several biophysical parameters were used to study urban cover in order to identify the characteristics of surfaces with regard to their physical and thermal behaviours using remote sensing data. These parameters were surface albedo and four common indices, NDVI, MNDWI, NDBI, and NDBal. Surface albedo (SA) is defined as the ratio of reflected to incident solar radiation (8, 9). It plays an important role in determining the energy balance of the ground surface (10), the radiative balance of the earth’s atmosphere (8), and urban climate and ecosystems (11). Many studies have examined the relationship of SA with various biophysical parameters, such as surface temperature. This relationship has been examined using field measurements and, more recently, by remote sensing data, with the latter applied especially in urban areas to assess urban thermal environments. Decreases in albedo values increase radiative energy absorption by man-made surfaces, leading to increases in surface and air temperatures that contribute to the formation of urban heat islands (12).

The relationship of LULC categories to various biophysical parameters such as land surface temperature have been intensively studied in terms of urban environment, urban climate, and urban heat islands. In this study, the SA is examined in relation to characteristics of LULC surfaces as a new approach, with the aim being for this to contribute in monitoring and evaluating urban environments and related issues.

Remote sensing, biophysical parameters and statistical analysis methods were thus combined to examine the relationships between SA and LULC types as represented by the NDVI, MNDWI, NDBI and NDBal indices in a semi-arid region. More specifically, the study aimed to (a) derive SA from multispectral imagery and (b) compute the area’s biophysical parameters using an indices-based image.

2. Methods

2.1. Study area and data

The city of Baghdad, in Iraq, was selected as the study area for this work. The geographical location for the study area (Figure 1) is between 33° 10.77' N and 33° 29.26' N and between 44° 11.55' E and 44° 34.23', with a total area of approximately 870 km². This region has a hot arid and subtropical desert climate based on Köppen’s climate classification system; the weather is particularly sunny and hot during the summer (13).
A Landsat 8 image acquired on 9th of August 2018 was obtained from U.S. Geological Survey. This image included six visible and near infrared bands, two TIR bands, and one panchromatic band at spatial resolutions of 30 m, 100 m, and 15 m, respectively. The image was pre-processed by the USGS Centre to correct for radiometric and geometric distortions. Dark object subtraction (DOS) was then used for atmospheric correction in a two-step process performed using ENVI 5.1 software (14):

1. Conversion of the digital numbers to the top of atmosphere reflectance.
2. Removal of the atmospheric effects from the image by subtracting the values of the darkest pixels from all pixels.

2.2. Retrieval of surface albedo

The values of SA were computed from the DN values of visible bands 2 and 4, near infrared band 5, and SWIR 1 band 6 and SWIR 2 band 7 from the Landsat 8 image. ENVI 5.1 Software was used to rescale the DN values to the Top of Atmosphere reflectance, with a range from 0 to 1. The SA was computed for the Landsat 8 image as per equation (1), using the TOA reflectance values as suggested by Liang (15). The values of SA ranged from 0 to 1:

\[
\alpha = \frac{(0.356 \times a_2) + (0.130 \times a_4) + (0.373 \times a_5) + (0.085 \times a_6) + (0.072 \times a_7) - 0.018}{1.016} 
\]

(1)

where \( a_i \) is the top of atmosphere reflectance values for bands 2, 4, 5, 6, and 7 of Landsat 8, and \( \alpha \) is surface albedo.

2.3. Calculation of Indices

Indices are important biophysical parameters that can be used in studying the characteristics of various land surfaces. The indices considered in this study were

1. Normalised Difference Vegetation Index (NDVI)

The NDVI is used to highlight vegetated surfaces in order to describe vegetation characteristics such as green biomass and chlorophyll content. It is computed using the red and near infrared bands as per equation (2). NDVI values range between -1 and 1 (16):

\[
\text{NDVI} = \frac{(R_{\text{NIR}} - R_{\text{Red}})}{(R_{\text{NIR}} + R_{\text{Red}})} 
\]

(2)

where \( R_{\text{Red}} \) = the spectral reflectance of red band

\( R_{\text{NIR}} \) = the spectral reflectance of near infrared band

2. Modified Normalised Difference Water Index (MNDWI)

Water bodies were determined using the modified normalised difference water index (MNDWI), was developed by Xu (17). This is calculated using the green and SWIR_1 bands, as shown in equation (3), and its value ranges from -1 to 1:
MNDWI = (R_{\text{Green}} - R_{\text{SWIR}-1}) / (R_{\text{Green}} + R_{\text{SWIR}-1}) \quad (3)

where $R_{\text{Green}}$ = the spectral reflectance of green band
$R_{\text{SWIR}-1}$ = the spectral reflectance of short-wave infrared band.

3. Normalised Difference Build-up Index (NDBI)

The NDBI was used to map the urban areas automatically (18):

$$\text{NDBI} = \frac{R_{\text{SWIR}-1} - R_{\text{NIR}}}{R_{\text{SWIR}-1} - R_{\text{NIR}}} \quad (4)$$

where $R_{\text{SWIR}-1}$ = the spectral reflectance of short-wave infrared band
$R_{\text{NIR}}$ = the spectral reflectance of near infrared band

4. Normalised Difference Barren Index (NDBaI)

This index was suggested by Zhao (19), who used it to classify bare lands based on different values of NDBaI.

$$\text{NDBaI} = \frac{R_{\text{SWIR}-1} - R_{\text{TIR}}}{R_{\text{SWIR}-1} - R_{\text{TIR}}} \quad (5)$$

where $R_{\text{SWIR}-1}$ = the spectral reflectance of short-wave infrared band
$R_{\text{TIR}}$ = the thermal infrared band.

3. Results and Discussion

Figure 2 shows the spatial distribution of each biophysical parameter within the study area. The values of the SA, NDVI, MNDWI, NDBI, and NDBaI ranged from 0.058 to 0.72, -0.3 to 0.68, -0.49 to 0.53, -0.54 to -0.25, and -0.7 to 0.26, respectively. The results indicate that high SA areas were associated with built-up and bare land areas (Figure 2a), which cover a large portion of the study area. In contrast, areas of lower SA values are associated with vegetation and water bodies (Figure 2a), represented here by the river, the dense orchards on both sides of the river bank, and the agricultural fields.
Figure 2. Spatial distribution patterns of biophysical parameters: (a) SA; (b) NDVI; (c) MNDWI; (d) NDBI; (e) NDBal.

Figure 3(a-d) shows the results of statistical analysis of the SA and each of the landscape indices. From the scatter plot in Figure 3(a), there is a moderate correlation between the NDVI and SA ($r = 0.4$), while the correlations between SA and NDBI and NDBal were strong ($r = 0.62$ and $r = 0.95$), as seen in Figure 3(c) and (d), respectively. However, a strong negative correlation was found between SA and MNDWI ($r = -0.81$) as shown in Figure 3(b).
The relationship of SA with land cover surfaces is thus different for the various parts of the study area of Baghdad. The strong relationship between SA and bare land is related to characteristics of bare land surfaces, which offer high reflection of solar incident radiation. This result is consistent with a previous study was conducted by Li (20), who pointed out that decreased soil moisture leads to increased SA values, and vice versa, as soil moisture absorbs more solar radiation.

With regard to vegetation, a moderate correlation was found between the SA and vegetation cover. A number of studies have revealed that there is a variation in SA values with vegetation, due to the varying characteristics of vegetation cover, including water content and density. A study conducted by Münch (21) found that the relationship of SA with NDVI (vegetation cover) may be positive or negative depending on the location and growing season.

The relationship between SA and built-up areas was strongly positively correlated. A number of other studies have confirmed that the thermo-physical properties of built-up surfaces have a significant influence on the value of SA. In addition, SA has an inverse correlation with land surface temperature, especially for

**Figure 3.** Scatter plots of surface albedo (SA) vs. landscape indices: (a) NDVI; (b) MNDWI; (c) NDBI; and (d) NDBal.
urban areas. In this context, cities represent large areas of heterogeneous surfaces in terms of thermo-physical properties; thus, the ability of built-up surfaces to reflect and absorb solar radiation also differs. It can be inferred that man-made surfaces with high reflectance of radiation have low surface temperatures, however, and thus the SA can be used as an effective parameter in studying the climate and environment of urban areas.

For water bodies, a negative correlation was found between SA and MNDWI. Water bodies showed the lowest SA values among all land cover categories over the study area, as shown in Figure 2(a). According to Hamoodi (2) water bodies have low reflectance and high absorption of solar radiation; however, certain characteristics of water such as heat capacity, purity, and depth can affect the relationship between SA and MNDWI.

4. Conclusion

The relationships of surface albedo with several biophysical parameters were examined using remotely sensed data. The following biophysical parameters of major land cover categories were considered in this regard: NDVI, NDBI, NDBal, and MNDWI.

Retrieving the SA and biophysical parameters from Landsat data offered the potential to analyse the extracted information with regard to urban cover and to link this with the local, regional, and global climate and environment data.

The results showed that SA is a significant indicator for studying urban areas, which in turn can play an important role in mitigating the influence of increased surface and air temperatures, especially in hot urban areas.

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