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Evaluating the Impact of Land Use/Land Cover Changes on the Surface Urban Heat Island intensity: The case study of Kabul city, Afghanistan

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Abstract

The purpose of this paper is to detect the areas which are affected by urban heat island (UHI) based on the relationship between land surface temperature and land use /land cover (LU/LC) changes during 1998, 2011, and 2020 for the major city of Kabul, the capital of Afghanistan, using multispectral and multi-temporal Landsat data (TM and OLI/TIRS). To achieve the objectives, the emissivity corrected land surface temperature method was examined to calculate Land Surface Temperature (LST), and the Land-use/Land-cover map was prepared using the support vector machine (SVM) supervised algorithm. The LU/LC was categorized into five major classes (vegetation, water-body, built-up, bare-land, and soil). According to the LST map estimated by processing the thermal band of the satellite image, areas influenced by Urban Heat Island (UHI) were detected to evaluate their anomalies to the existing LU/LC types. The findings of LST illustrate, that the mean recorded LST in 1998 was 39.42˚C, whereas the mean recorded LST in 2020 was 41.25˚C, which demonstrates a 1.83 ˚C increase for the whole study period. Specifically in 1998 only five districts (1,16,9,15, and 19) were affected by surface UHIs, while in 2011, the surface UHIs influenced areas increased to eight districts (15, 16, 1, 21, 17, 12, 13, and 8), and in 2020, the surface UHIs affected regions are improved to ten districts (1,19, 15,16, 9,17, 22, 11, 13, and 2) over the Kabul City. These variations and improvements are mostly due to the status of LU/LC in the study area, and it demonstrates the strong link between land cover and land surface temperature. Furthermore, Normalized difference vegetation index (NDVI), and normalized difference built-up index (NDBI) were also extracted. The relationship of NDVI and NDBI with LST was evaluated. Based on the results, a strong negative relationship between LST and NDVI was observed, while a positive relationship between LST and NDBI was recorded. The findings of this work show that an increase in non-evaporation areas and a decline in the greenery surfaces increased the LST. Consequently, the outcomes of this study are significant for decision-makers and urban planners to manage the drawbacks of urbanization temperature in arid and semi-arid areas.

Keywords: LU/LC changes, Urban Heat Island (UHI), Landsat Image, SVM

1. Introduction

The global urban expansion expressed in 2018 by (Huang et al., 2021) shows an increase in the total land surface by 0.54%. Predictably, 2/3 of the overall population will be intense in urban areas by the mid-twentieth century (Kamali Maskooni et al., 2021). This can tell us that 2/3 of the overall population will experience increased temperature due to UHI along with global warming effects. In this case, LU/LC changes can be taken into account as two main factors for environmental monitoring, urban planning, and land management(Kamali Maskooni et al., 2021). The UHI effects are taken into account as one of the key environmental consequences of urbanization, a phenomenon that increases the temperature of the urban area significantly compared to nearby rural areas(Gašparović et al., 2021; Gusso et al., 2015; Luo & Wu, 2020; Naim & Kafy, 2021a; F. Yuan & Bauer, 2007; Zhou & Chen, 2018). Some undesirable impacts of the urban heat island include air pollutant emanation, increased energy consumption, and greenhouse gases triggering harmful environmental effects on people's health and life comfortability(Simwanda et al., 2019). Furthermore, due to the increase of detrimental emissions, the level of surface ozone is much higher in the urban environment compared to the ruler area. This may cause higher urban temperatures which decrease the air quality. Literature showed that ozone contamination can intensify certain lung illnesses(Mohammad Harmay et al., 2021; Naim & Kafy, 2021a, 2021b).

On the other hand, alterations in the built-up ecological environment caused by unplanned urbanization can straightly affect health and living standards(Gerlitz et al., 2018).

Literature e.g. (Dihkan et al., 2015; Umezaki et al., 2020; Y. Yuan et al., 2017) have shown that the rising land surface temperature caused by urbanization due to the degradation of naturally vegetated areas, especially in unplanned cities is a very serious problem. The alterations in land use and land cover pattern affect the whole urban environment including urban hydrology, evaporation rates, and land surface temperature (Correia Filho et al., 2019; Dihkan et al., 2018; Rajasekar & Weng, 2009). UHI is taken into account as one of the very significant outcomes driven by urbanization and human activities inclined by land-use patterns and it characterizes the changes in albedo, heat flux altercation, and roughness of land surface (Correia Filho et al., 2019; Dihkan et al., 2018; Rajasekar & Weng, 2009). The arid and semi-arid regions are probably more prone to the effects of UHI. These regions experience extreme temperatures due to a lack of rainfall in the summer season(Kamali Maskooni et al., 2021).

Central Asia countries including Afghanistan, Kazakhstan, Uzbekistan, Turkmenistan, Tajikistan, and Kyrgyzstan, are considered extremely continental climates (Gerlitz et al., 2018). They are typically counted as arid and semi-arid regions due to less rainfall during the summer season compared to the north and south Asia countries (Gerlitz et al., 2018). Among them, Afghanistan has a climate of hot summers and cold winters. The lowest precipitation of around 30 mm per year takes place in the southwestern and the highest precipitation of more than 100 mm takes place in the northeastern regions. The temperature gradually increases from the northeastern to the southwestern plateau zone (Manawi et al., 2020). Kabul is the capital of Afghanistan, the biggest city in Afghanistan with increasing inhabitants and densification of the built-up area as well as the increasing industries (Ahmadi & Kajita, 2017; Zahid et al., 2019). The increasing of built-up areas and urban heat islands effects especially in Kabul city considered undesirable consequences for the population.

Thus, it is very important to rapidly analyze and assess the impact of urbanization on urban environmental alterations. It can deliver a scientific source for government and non-government organizations for deciding to alleviate the drawbacks of urbanization on the living environment.

Reviewing the literature shows that the new technologies such as GIS and Remote Sensing have advantages of wide range coverage, high spatial and temporal resolutions, and high precision compared with conventional observation methods, which brings the facility of evaluation of a large scale of the urban ecological environment (Dissanayake et al., 2019a; Hoan et al., 2018; Kamali Maskooni et al., 2021).

Moreover, the remotely sensed data provides an effective basis for urban environmental evaluation at altered times and scales. Different systems have been suggested for acquiring remotely sensed data, where the utmost broadly used system is using satellite data. For instance, the Landsat satellite constellation data are freely available and provided by the United States geological survey (USGS). In recent times, different types of remotely sensed data are used for assessing several parts of urban ecological and environmental conditions. For example, NDBI, NDVI, NDWI, biophysical composition index (BCI), and some other indices can characterize the urban ecology and environment from different characteristics. The satellite constellations with multispectral sensors provide data that can deliver a consistent scheme for mining different information about the ecological environment, comprising the biophysical composition index, vegetation index, humidity, and impermeable surface indices(Gašparović et al., 2021; Piyoosh & Ghosh, 2018)

The new technologies which retrieve the LST from thermal infrared data have been considerably developed since the beginning of twenty century, and now it is broadly applied in various industries(Abdullah-Al-Faisal et al., 2021). Currently, the relationships between LST and LULC using GIS and remotely sensed data are investigated by many studies at global and local scales(Dey et al., 2021; How Jin Aik et al., 2021; Naim & Kafy, 2021b; Ogunjobi et al., 2018).

Although, insufficient studies were conducted to study UHI in arid and semi-arid areas experiencing extreme surface temperature during the summer season due to lack of rainfall and humidity. Kabul city which is one of the major cities of Afghanistan is placed in the semi-arid and arid region, and the pressure of quick urban expansion and inhabitants growth (J. F. He et al., 2007; Kamali Maskooni et al., 2021; Lo & Quattrochi, 2003; Manawi et al., 2020).

Since Kabul city has urbanized rapidly, most of the green areas have been constantly replaced with impervious surfaces (Chaturvedi et al., 2020). Besides that, many of the tallest buildings in Kabul city are illegal and oppose with norms and standards of a planned city. Built areas, industrial companies, and especially the unplanned illegal tall buildings in Kabul city, produce a high amount of heat during the summer season. To reduce UHI efficiently and safely, it is essential to consider the impact of LU/LC changes on land surface temperature.

Various scholars had evaluated the air quality of Kabul City (Ayoobi et al., 2022; Stiftung, 2010; Waseq, 2020). The conducted works in general concentrated on particular matters, to evaluate the air quality over the Kabul City. Furthermore, the impact of buildings' energy consumption on air quality, and the causes of air pollution in Kabul City related to transportation and groundwater were also examined. However, the evaluation of surface UHIs based on the relationship between land surface temperature and Land Use/Land Cover Changes in an arid and semi-arid urban region, is lacking. Therefore, this is the first remotely sensed research to quantify and evaluate surface UHIs based on the relationship between land surface temperature and Land Use/Land Cover changes over the Kabul City.

Consequently, the specific objectives of this study are (1) to evaluate the LU/LC changes, (2) to examine the LST changes, (3) to create the relationship between LU/LC and LST, (4) to detect the UHIs affected areas, and (5) to assess the relationship of NDVI and NDBI with LST over the Kabul city the capital of Afghanistan.

2. Materials and methods

2.1 Study Area

Kabul, which is the capital and the biggest city of Afghanistan, is situated in the eastern portion of Afghanistan at 34°31′31″ North latitude and 69°10′42″ East longitude as shown in (**Figure 1**). Kabul is also a municipality forming a part of the Kabul Province. Kabul city is classified into 22 districts. The population of Kabul city has increased from 1.5 million in 2001 to around 5 million people in 2017, which become the fifth fastest-improving city in the world(Chaturvedi et al., 2020). Rapid urbanization has been unable to cope with the demands of the increasing population in a capital city that was planned to hold about 700,000 people(Chaturvedi et al., 2020). This reason prepared the way, that around 70 percent of housing in Kabul city has been developed illegally(Guardian, 2014). Illegal housing in Kabul, where approximately 6 million people live, is regarded as one of the reasons for rising air pollution levels in 2020(Humanitarian, 2020). The climate of Kabul city ranges from dry to semi-arid, with warm summers and cold winters. In the winter, the land surface temperature might drop below -10° C, while in the summer it can reach 40° C (Qutbudin et al., 2019). Approximately 56 percent of Kabul's land is covered by mountains, while 38 percent is flat. Kabul has four dry seasons, with the most rain falling in February, March, and April. The maximum yearly rainfall recorded in Kabul is 400mm (Mehrad, 2020).

[Insert Figure 1]

2.2 Data sources and preprocessing

To evaluate the impact of surface urban heat island on different LU/LC types, Multispectral data of Landsat-5 Thematic Mapper (TM) and Operational Landsat Imager (OLI) Landsat-8 along with infrared sensors (TIRS) for 1998, 2011, and 2020 (July-August period) with less than 3% cloud cover were obtained from the United States Geological Survey (USGS) website as demonstrated in (**Table 1**). Because of probable sensor disturbances due to unfavorable weather conditions at the time of imaging, raw satellite images may require some corrections. Therefore, before processing, the satellite images must be corrected (Dissanayake et al., 2019b). The Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercube (FLAASH) method was used to perform atmospheric correction using the ENVI 5.3 software as a preprocessing step. Moreover, for all images, multispectral band data were transformed to surface reflectance, whereas thermal band data were converted to at-sensor brightness temperature in degrees Celsius. The pre-processing steps were performed for the satellite data before the LU/LC and LST classification and retrieval.

[Insert Table 1]

2.3 LST estimation

The emissivity corrected land surface temperature method which requires the input of emissivity values from different surfaces was used in this study. First, this method entails the conversion of brightness temperature to spectral radiance using the following formula:

$$L_{\lambda} = M_L Q_{cal} + A_L \quad (1)$$

where L_{λ} is the top of atmospheric spectral radiance W/m^2·sr·µm, M_L is the band-specific multiplicative rescaling factor from the metadata, Q_{Cal} is quantized and calibrated standard product pixel values (DN), and AL is the band-specific additive rescaling factor from the metadata.

The next step is to transform Spectral Radiance to Temperature in Kelvin with the following formula:

$$BT = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda} + 1\right)} \quad (2)$$

In equation (2), BT stands for the brightness temperature in Kelvin, K_1 and K_2 is the specific thermal conversion constant which is taken from the metadata. To compute the LST, we first determined the land surface emissivity (ε) as described by (Dissanayake et al., 2019a) and (Naim & Kafy, 2021b) as following:

$$\varepsilon = mP_V + n \quad (3)$$

Where ε is the land surface emissivity, n=0.004, m=0.986, and Pv is the proportion of vegetation (Hua & Ping, 2018; Kamali Maskooni et al., 2021):

$$Pv = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} + NDVI_{min}}\right)^2 \quad (4)$$

Normalized Difference Vegetation Index (NDVI) indicates the degree of greenness over an area. A healthy environment condition is characterized by the positive values of NDVI. NDVI plays an important role in urban climate analysis(Guha et al., 2020; M. O. Sarif & Gupta, 2019). In general, remote sensing-based vegetation cover monitoring depends on the characteristics of chlorophyll and the electromagnetic spectrum. The NDVI is considered the most significant index in vegetation cover extractions. The NDVI has been widely utilized in studies to determine the extent of vegetation cover(Chandramathy & Kitchley, 2018). The equation (5) was used to determine the NDVI.

$$NDVI = \frac{NIR - Re\,d}{NIR + Re\,d} \quad (5)$$

Many studies including (Weng et al., 2004) have been used the following equation to estimate the LST in °C after estimating the at-satellite brightness temperature and land surface emissivity from Equation (2).

$$LST = \left(\frac{BT}{\{1 + \left[\left(\lambda \frac{BT}{\rho}\right) * ln\varepsilon\right]\}}\right) - 273.15 \quad (6)$$

In equation (6), LST stands for land surface temperature (Celsius), BT stands for the brightness temperature in Kelvin, λ is the wavelength of emitted radiance (λ = 10.8 μm), $\rho = h \times c/\sigma (1.438 \times 10^{-2}$ m K), h = Planck's constant (6.626×10^{-34} Js), c = velocity of light (2.998 × 108 m/s), and σ = Boltzmann constant (1.38×10^{-23} J/K). The outcome of LST for the current study can be seen in (Figure 2).

[Insert Figure 2]

2.4 Land-use/land-cover classification and accuracy assessment.

To extract and classify LU/LC variations in the study area during 1998, 2011, and 2020 respectively, and to find out their relationships with the spatial patterns of LST, visible and near-infrared bands of Landsat TM and OLI/TIRS images were subjected for classification of LU/LC using support vector machine supervised classification algorithm in ENVI 5.3 software and the results were exported to ArcGIS 10.7 for further statistical analysis. Kabul city was classified into five categories: Built-up, Vegetation, Water-body, Bare-Land, and Soil as shown in (**Figure 3**). Due to classification algorithms and image-gathering processes, land cover maps sometimes contain errors (Ogunjobi et al., 2018). Therefore, The assessment of classification accuracy was done to validate the accuracy of classified maps and evaluate the performance of the classifier used. In this research, the kappa coefficient was utilized to evaluate the classification accuracy of the LU/LC maps by selecting more than 350 checkpoints on the classified maps as well as on the ground.

[Insert Figure 3]

2.5 Calculation of normalized difference built-up index (NDBI)

NDBI is one of the most important indices for understanding urban climate. NDBI is a widely-used index for the evaluation of built-up statuses(Kamali Maskooni et al., 2021). NDBI values are related to spectral signature, which ranges from medium-infra-red to near-infra-red bands. As well as it is useful for mapping human settlements(C. He et al., 2010). Hence, in this study, NDBI is estimated for three intervals (1998, 2011, and 2020). NDBI can be calculated by the following formula.

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \quad (7)$$

3. Result and discussion

3.1 Accuracy assessment of LU/LC classification

As previously stated, Kabul city was categorized into five distinct LU/LC classes (Built-up, Vegetation, Water-body, Bare-Land, and Soil) using the support vector machine method in 1998, 2011, and 2020 respectively. The outputs of the accuracy assessment are demonstrated in **Table 2**. Based on **Table 2**, the overall accuracy of the land cover maps for 1998, 2011, and 2020 were 91%, 90%, and 88% respectively, which is higher than the standard threshold of 85 percent (Eniolorunda et al., 2017). The Kappa coefficients for 1998, 2011, and 2020 were also estimated to be 0.88, 0.86, and 0.85 respectively. According to (Klein Goldewijk & Ramankutty, 2004), a Kappa coefficient of higher than 0.85 indicates strong agreement between images and ground data.

[Insert Table 2]

3.2 LU/LC classification and change in patterns between 1998 and 2020

Figure 3 demonstrates the spatial pattern of LU/LC classification for the study region in 1998, 2011, and 2020 respectively, created by the support vector machine algorithm. As previously stated, the entire domain was classified into five categories. **Table 3** describes the estimated area and percentage of each land-use type, as well as a summary of LU/LC variations over the studied period, is presented in **Table 4** . A minus (−) sign in **Table 4**, exposes a decline in a particular land-use type, while a plus (+) sign shows an increase compared to the earlier time step. The outputs reveal that between 1998 and 2011, the built-up areas expanded by 2.9%, from 19.1 km^2 to 24.9 km^2, which shows a 5.8 km^2 expansion, whereas between 2011 and 2022 the built-up area increased by 2.9%, from 24.9 km^2 to 31.2 km^2, which shows 6.4 km^2 increase (**Table 3** and **Table 4**). Moreover, the soil class decreased by 18.3% between 1998 and 2011, which expose a 36.5 km^2 reduction, while between 2011 and 2020 the output exposes a 12.5% increase. However, the bare lands increased dramatically by 19.2%, from 93.9 km^2 to 131.8 km^2 between 2011 and 2020 (**Table 3** and **Table 4**). Furthermore, the total vegetation area declined slightly by 3.7%, from 18 km^2 to 11.0 km^2 between 1998 and 2011, while between 2011 and 2020 the result shows a 3.4% reduction, from 11 km2 to 4.1 km2, which shows a 6.9 km^2 decrease. However, the water body decreased by 0.2% from 0.5 km^2 to 0.2 km^2 between 1998 and 2011, whereas between 2011 and 2020 the water body increased by 0.016%, from 0.23 km^2 to 0.28 km^2, which shows a 0.05 km^2 increase. The results of LULC variation demonstrate that the spatial range of the built-up area of Kabul city expanded from 1998 to 2020. The expansion of built-up areas in Kabul city has a balanced pattern throughout the city. Soil and vegetation land cover changed to impervious surfaces such as built-up areas and bare lands. As a result, growing urbanization hurts the city's temperature-stabilization zones.

[Insert Table 3]

[Insert Table 4]

3.3 Relationship between land use/land cover and LST

The LST map prepared from Landsat TM, and TIRS satellites are demonstrated in **Figure 2**. The surface temperature in this map was categorized using standard deviation, and the locations influenced by UHI were identified. The summary of the statistical analysis of LST is presented in **Table 5**. Based on that, the outputs reveal that LST fluctuated from 18.48 to 49.6°C, 21.5-51°C, and 22 – 52.19 °C during 1998, 2011, and 2020 respectively. Furthermore, the mean LST increased from 39.42 to 41.57°C between 1998 and 2020, whereas it changed from 40.57°C to 41.25°C between 2011 and 2020 respectively (**Table 5**). Moreover, based on zonal statistical analysis in ArcGIS the mean LST for each LU/LC type is estimated and the outputs are demonstrated in **Table 6.** According to **Table 6**, the outputs reveal that bare land has the maximum LST value, whereases the water body has the minimum value. The land surface temperature for bare land is changed from 38.43°C to 41.89°C which shows 3.46°C changes between 1998 and 2020, while, LST for water body is changed from 25.24°C to 27.42°C which shows a 2.18°C increase for the whole period. The LST for vegetation areas decreased by 1.65°C from 1998 to 2020, while a 2.02°C increase was estimated between 1998 and 2011, and a 3.67°C decrease was estimated between 2011 and 2020. The LST for built-up areas declined by 1.28°C for the whole period, while a 0.4°C increase was estimated between 1998 and 2011 and a 1.67°C decrease was estimated between 2011 and 2020. The LST for soil cover is changed from 42.51°C to 42.88°C, which expose 0.38°C changes between 1998 and 2020, while a 1.16°C increase was estimated between 1998 and 2011, and a 0.79°C reduction was estimated between 2011 and 2020. Based on the overall assessment of **Table 6**, the outputs expose that the maximum increase of LST is related to bare land, built-up, and urban areas, whereas the minimum increase of LST is related to the water body and vegetation areas. This is related to the high evapotranspiration phenomenon from vegetation areas which precisely play important role in the reduction of land surface temperature(Kamali Maskooni et al., 2021; M. O. Sarif & Gupta, 2019). Moreover, the water body is also playing an important role in the evaporation and cooling process which can have a high hand in the reduction of land surface temperature(Bokaie et al., 2016; Paper, 2016; Y. Yuan et al., 2017).

The summary of statistical analysis of mean LST spatial variations for all districts over the Kabul City is shown in **Figure 4**. Based on that, the maximum mean LST in 1998 is estimated for 1, 16, 9, 15, and 19 districts, while in 2011 the highest mean LST value is estimated for 15, 16, 1, 21, 17, 12, 13, and 8 districts, and in 2020 the maximum LST value is calculated for 1,19, 15,16, 9,17, 22, 11, 13, and 2 districts. The LST change is related to urban growth and LU/LC changes which have a direct impact on the UHI of the city(Balew & Korme, 2020; Correia Filho et al., 2019). Based on **Figure 4**, in 1998 five (1,16,9,15, and 19) districts were highly affected by surface UHIs, while in 2011 it increased to eight (15, 16, 1, 21, 17, 12, 13, and 8) districts which are affected by UHIs, and in 2020 the affected UHIs regions are improved to ten (1,19, 15,16, 9,17, 22, 11, 13, and 2) districts. Furthermore, the outputs revealed that surface UHIs over the Kabul City are in the developing process and this development will have negative impacts on both people and the environmental condition of the Kabul City.

The reduction of green areas, development of urban areas, expansion of imperviousness surfaces, the existence of industrial parks, factories that use poor quality fuel, brick factories that use row coal, informal residential settlements, and Kabul International Airport are the main catalyst in the development of surface UHIs over the Kabul City.

[Insert Figure 4]

Therefore, to mitigate the UHIs expansion over the Kabul City, the development of green zones, usage of energy efficiency approaches in building designs and construction, and also the comprehensive utilization of green roofs, urban parks, street trees, and renewable energy resources, are suggested. Moreover, imposing heavy penalties for the owners of those factories who use poor quality fuel and raw coal will also have a positive impact on the reduction of surface UHIs over Kabul City.

[Insert Table 5]

[Insert Table 6]

3.4 Relationship between NDVI and LST

NDVI is the most commonly used vegetation index for observing greenery around the world. In general, healthy vegetation absorbs the electromagnetic spectrum well in the visible region. The index has also been utilized in several UHI types of research because of the cooling impact of vegetation due to latent heat vaporization and convective cooling of tree canopies that support the air-cooling process(Bokaie et al., 2016, 2019). Therefore, in this study NDVI is calculated for three intervals (1998, 2011, and 2020), the results are shown in **Figure 5**. The statistical analysis is shown in **Table 7**. An NDVI between 0.1 and 0.7 is generally related to vegetation areas, whereas an NDVI greater than 0.75 is related to canopy cover. The NDVI values which are near zero are related to bare land and soil, while the NDVI negative values are water indicators (Kamali Maskooni et al., 2021).

Based on **Figure 5** and **Table 7**, the outputs revealed, that the mean NDVI value for the whole study area was 0.16, 0.15, and 0.2 in 1998, 2011, and 2020 respectively. The highest mean NDVI value is estimated in district 14, while the lowest mean NDVI is estimated for district 1 in 1998. In 2011 the highest mean NDVI value is also estimated for district 14, while the lowest mean NDVI value was estimated for district 20, and in 2020 the highest mean NDVI value is estimated for district 14 whereas the lowest NDVI mean value is calculated for district 1 and district 21 of Kabul city. Therefore, in general, lower values for NDVI are estimated in areas that are composed of bare land, built-up, and soil covers. The findings of NDVI estimation revealed that this parameter generally reduced during 22 years of studying period, which indicates the LU/LC changes from green areas to built-up covers. The relationships between LST and NDVI were investigated using correlation analysis which is shown in **Figure 6**. Based on that, the findings expose that the lower NDVI values were estimated in areas represented by higher land surface temperature. However, there is a strong negative correlation between NDVI and LST for all time intervals with a correlation coefficient of R^2=0.44, 0.30, and 0.32 in 1998, 2011, and 2020 respectively. Hence, due to the negative correlation between NDVI and LST, it can be stated that a reduction in vegetation cover results in an improved surface temperature(Naim & Kafy, 2021a; Ogashawara & Bastos, 2012; Md Omar Sarif et al., 2020; Umezaki et al., 2020; Weng et al., 2004).

[Insert Figure 5]

[Insert Table 7]

[Insert Figure 6]

3.5 Relationship between NDBI and LST

The value of NDBI generally differs from -1 to +1. Literature review shows that the NDBI negative values donate water bodies and vegetation covers, whereas the positive values refer to the built-up area, and the lower positive values specify bare land cover. in general, NDBI gives information regarding the imperviousness of the surface(Md Omar Sarif et al., 2020). In this study, the estimated NDBI for three-time steps (1998, 2011, and 2020) is shown in **Figure 7**, and the statistical summary is described in **Table 8**. Based on that, our findings revealed, that the mean NDBI value increased from -0.08 in 1998 to -0.06 in 2011, and -0.03 in 2020 respectively for the whole Kabul city. Moreover, the outcomes donated that, the lowest mean NDBI is estimated in 17, 1, 11, and 22 districts of Kabul city, while the highest mean NDBI is calculated for 10, 18, and 9 districts in 1998. In 2011 the minimum mean NDBI is estimated for 17, 1, 22, and 11 districts, while the maximum mean NDBI is estimated for 18, 9, and 10 districts respectively, and in 2020 the highest mean NDBI is calculated for 1, 17, 21, 13, and 22 districts, while the lowest NDBI is estimated for 18, 14, and 9 districts of Kabul city respectively. Based on **Figure 8,** our findings revealed a strong positive relationship between LST and NDBI for all time intervals, with a correlation coefficient of R^2=0.31, 0.24, and 0.32 in 1998, 2011, and 2020 respectively.

[Insert Figure 7]

[Insert Table 8]

[Insert Figure 8]

4. Conclusions

This paper evaluated the impacts of LU/LC change on surface UHI based on LST for three intervals (1998,2011, and 2020) over Kabul City, the capital of Afghanistan using multispectral and multi-temporal Landsat data (TM, OLI and TIRS). The emissivity corrected land surface temperature method was used for extraction of LST to analyze UHIs in the city, and the support vector machine (SVM) supervised algorithm was used to prepare the LU/LC maps for all study periods respectively. The satellite images were radiometrically and atmospherically corrected before performing the desired processing to produce LST, LU/LC, NDVI, and NDBI by the use of ENVI 5.3 software. The findings of LST illustrate, that the mean recorded LST in 1998 was 39.42˚C, whereas the mean recorded LST in 2020 was 41.25˚C, which demonstrates a 1.83 ˚C increase for the whole study period. The study area was categorized into five major classes (vegetation, Water-body, built-up, bare-land, and soil). Hence, the findings of LU/LC variations between 1998 and 2020 indicate that vegetation areas declined from 14.20% to 3.57 %, whereas built-up areas increased from 18% to 43.56%. In addition, water bodies declined from 0.52 % to 0.27%, while bare land increased from 24.17% to 35.64%, and finally, the soil cover decreased from 42.76% to 16.96%. The mean LST of each LU/LC class was also extracted to assess the distributed LST changes. According to that, the maximum increase of LST is recorded for bare land, built up, and urban areas, whereas the minimum increase of LST is related to the water body and vegetation areas for all study periods respectively. This demonstrates the influence of natural covers such as water bodies and green areas on the mitigation of the intensity and spread of UHI. According to the overall assessment, the outputs revealed that surface UHIs over the Kabul City throughout the study period are developing. Based on results, in 1998 only five districts (1,16,9,15, and 19) were affected by surface UHIs, while in 2011 surface UHIs affected areas increased to eight districts (15, 16, 1, 21, 17, 12, 13, and 8) and in 2020 the UHIs affected regions are increased to ten districts (1,19, 15,16, 9,17, 22, 11, 13, and 2) which demonstrates ascending development of UHIs over the Kabul City. Additionally, the obtained results also confirmed an adverse correlation between the spatial pattern of land cover and green spaces, measured by NDVI, and LST estimated by satellite images. As expected, with an increase in the NDVI, the LST was reduced and in areas covered with green spaces, a lower average LST was observed, while a positive correlation was found between mean LST and NDBI for all time intervals respectively. As expected, with an increase in the NDBI, the LST was also increased and in areas covered with built-up covers, a higher mean LST was recorded for all study periods respectively.

The conversion of green areas and water bodies to impervious surfaces like built-up areas and bare lands are the main parameters in the development of UHI, and also the existence of industrial parks, factories that use poor quality fuel, brick factories that use row coal, informal residential settlements, and Kabul International Airport are recognized as a catalyst for production and development of surface UHIs over the Kabul City.

Therefore, to mitigate the UHIs expansion over the Kabul City, the development of green zones, usage of energy efficiency approaches in building designs and construction, and also the comprehensive utilization of green roofs, urban parks, street trees, and renewable energy resources, are suggested. Moreover, imposing heavy penalties for the owner of those factories who use poor quality fuel and raw coal will also have a positive impact on the reduction of surface UHIs over Kabul City.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement (DAS)

The data used to support the finding of this study are included within the article.

Competing Interest Statement:

The authors declare they have no competing interests.

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The authors confirm their contribution to the paper as follows:

Ahmad Shakib Sahak carried out the statistical analysis of the spatial data in the ArcMap and drafted the manuscript. Karimullah Ahmadi carried out the atmospheric corrections and created land use land over of study area using ENVI 5.3 software. M. Sulaiman Fayez Hotaki carried out the literature review for the paper and helped to draft the manuscript. Prof. Dr. Fevzi Karsli participated in the design of the study and helped in the interpretation of the results. All authors read and approved the final manuscript.

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Figure Captions

Figure 1. Location of a) Kabul Province in Afghanistan, b) Kabul Province in Kabul City, c) RGB Map of Kabul City .... **Error! Bookmark not defined.**
Figure 2. Classified maps of land surface temperature of Kabul city in: a) 1998, b) 2011, and c) 2020.. **Error! Bookmark not defined.**
Figure 3.The LU/LC classification pattern of the study area in: a) 1998, b) 2011, and c) 2020 .... **Error! Bookmark not defined.**
Figure 4. Summary of mean land surface temperature for each district over the Kabul City. .... **Error! Bookmark not defined.**
Figure 5. Distribution of NDVI over Kabul city in: a) 1998, b) 2011, and c) 2020. .... **Error! Bookmark not defined.**
Figure 6. Correlation between LST and NDVI in 1998, 2011, and 2020. .. **Error! Bookmark not defined.**
Figure 7.Distribution of NDBI over Kabul city in: 1998, 2011, and 2020. **Error! Bookmark not defined.**
Figure 8. Correlation between LST and NDBI in 1998, 2011, and 2020. .. **Error! Bookmark not defined.**

Table Captions

Table 1. Details of Landsat images for selected study. .... **Error! Bookmark not defined.**
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Table 3. Land-use/land-cover areas in 1998, 2011 and 2020........ **Error! Bookmark not defined.**
Table 4. Land-use/land-cover changes of Kabul city 1998, 2011 and 2020**Error! Bookmark not defined.**
Table 5. Summary of LST (°C) for Kabul city from 1998 to 2020 .... **Error! Bookmark not defined.**

Table 6. Summary of mean land surface temperature for each land use and land cover type ....**Error! Bookmark not defined.**
Table 7. Summary statistics for NDVI for Kabul city during (1998-2020) study period. .... **Error! Bookmark not defined.**
Table 8. Summary statistics of NDBI for Kabul city during 1993 to 2020. **Error! Bookmark not defined.**

Figures

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Figure 8

Correlation between LST and NDBI in 1998, 2011, and 2020