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Land-Use/Land-Cover Changes and Its Contribution to Urban Heat Island: A Case Study of Islamabad, Pakistan

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Abstract: One of the essential anthropogenic influences on urban climate is land-use/land-cover (LULC) change due to urbanization, which has a direct impact on land surface temperature (LST). However, LULC changes affect LST, and further, urban heat island (UHI) still needs to be investigated. In this study, we estimated changes in LULC from 1993 to 2018, its warming (positive) and cooling (negative) effect, and their contribution to relative LST (RLST) in the city of Islamabad using satellite remote-sensing data. The LULC was classified using a random forest (RF) classifier, and LST was retrieved by a standardized radiative transfer equation (RTE). Our results reveal that the impervious surfaces has increased by 11.9% on the cost of declining barren land, forest land, grass/agriculture land, and water bodies in the last 26 years. LULC conversion contributed warming effects such as forest land, water bodies, and grass/agriculture land transformed into impervious surfaces, inducing a warming contribution of 1.52 °C. In contrast, the replacement of barren land and impervious surfaces by forest land and water bodies may have a cooling contribution of −0.85 °C to RLST. Furthermore, based on the standardized scale (10%) of LULC changes, the conversion of forest land into impervious surfaces contributed 1% compared to back conversion by −0.2%. The positive contribution to UHI due to the transformation of a natural surface to the human-made surface was found higher than the negative (cooler) contribution due to continued anthropogenic activities. The information will be useful for urban managers and decision makers in land-use planning to control the soaring surface temperature for a comfortable living environment and sustainable cities.

Keywords: land-use/land-cover changes; random forest; relative land surface temperature; warming and cooling contribution; sustainable future cities

1. Introduction

Human beings rather than natural forces are continuously involved in the exchange of energy from the earth's surface to the atmosphere through land-use/land-cover (LULC) changes [1,2], which has a direct impact on Land Surface Temperature (LST). The reasons for LULC changes are the growth both in population and urbanization in the cities. For instance, the rapid urbanization and population growth in the cities sprung out from 54.6% to 78.3% between 1950 and 2015 [3]. Urban land-use covered about 3% of the earth's land surface [4]. Urbanization involves LULC transformations of replacing soil and vegetation cover by impervious surfaces, agricultural activities, commercial and industrial operations, and low-density buildings replaced by high-rise complex urban structure [5–7].

Hence, urbanization induces natural land cover replaced with grey structures that modify the urban biophysical climate and alteration of LST [8]. Such transformation from natural surfaces to impervious surfaces has changed surface energy and radiation balance by increasing low heat transfer capacity [9]. As a result, a phenomenon known as the urban heat island (UHI) effect is developed due to the conversion of land surfaces, materials of the infrastructure, and heat release from anthropogenic activities [10].

Transformation of one land-use type to another, such as barren land to the built-up area or green space to impervious surface, may bring changes in surface energy [11,12]. Such rapid changes lead to significant changes in local climate, particularly having impacts on LST and local air temperature. In general, land-use composition and spatiotemporal patterns have a substantial effect on LST [10]. LST is one of the most fundamental physical factors which has been linked directly to LULC changes [13]. Due to vegetation losses in the metropolis of Beijing, Sun and Chen [14] investigated relative LST (RLST) values in Beijing from 2002 to 2012. Urbanization affects land-cover changes, which correspond to the RLST pattern [9]. For instance, Akbari and Kolokotsa [10] found a positive correlation between urban impervious surfaces and LST during the summer daytime.

LST can be quantified and assessed by using Geographic Information System (GIS) and remote sensing [15,16]. Assessment of LULC changes and its impact on LST will provide valuable information for urban planners and decision makers. Previous studies focused on LULC changes in the urban as well as in the rural mountain areas of Pakistan [1,17–21]. Still, few studies have reported the impact of independent LULC changes on associated RLST. The novel approach of this study is to illustrate the positive and negative effects of independent LULC conversion and its contribution to UHI over the region of Islamabad, Pakistan.

More specifically, the objectives are (1) to investigate LULC and associated surface temperature changes in the city of Islamabad during the period 1993 and 2018, (2) to assess the warming and cooling effects of independent land-use change, and (3) to compare the contribution of land-use/land-cover changes to UHI based on a standardized scale of 10%.

2. Materials and Methods

2.1. Study Area

The city of Islamabad is the capital of the Islamic Republic of Pakistan located between 33°28′12″ N latitude and 72°48′36″ E longitude. According to the United Nations World Urbanization Prospects (2018), the population had 40,000 in 1950, 110,000 in 1995, 678,000 in 2005, and 1.095 million in 2018 and is expected to be 1.67 million by 2030 [22]. These estimates represent the urban agglomeration of Islamabad, which typically includes Islamabad's population in addition to adjacent suburban areas. The city is planned by urban designer Constantinos A. Doxiadis and Doxiadis associates in the late 1950s and is becoming a fast-growing city. The city is a “unique” example of a large new city “planned for the future and built for the present”, fully respecting long-term planning [23]. It covers about 906 km², and the elevation ranges from 400 m to 650 m. The study area is classified into different zones/residential sectors (i.e., Zone 1–Zone V) as shown in the upper left side of the Figure 1. The climate is humid subtropical with five seasons: winter (November–February), spring (March–April), summer (May–June), monsoon (July–August), and autumn (September–October) [24]. June is the hottest month in Islamabad, and the highest temperature reached 46.5 °C, recorded in 2005. Temperatures peaked above 40 °C for four consecutive days in 2010. Over 1993–2012, there were eleven days when the temperature exceeded 44 °C and were recorded at 30 to 44 °C in 2018 in the summer days. The geology is composed of tertiary sandstone, limestone, and some alluvial deposits [25]. Figure 1 depicts the geographical location of the study area.

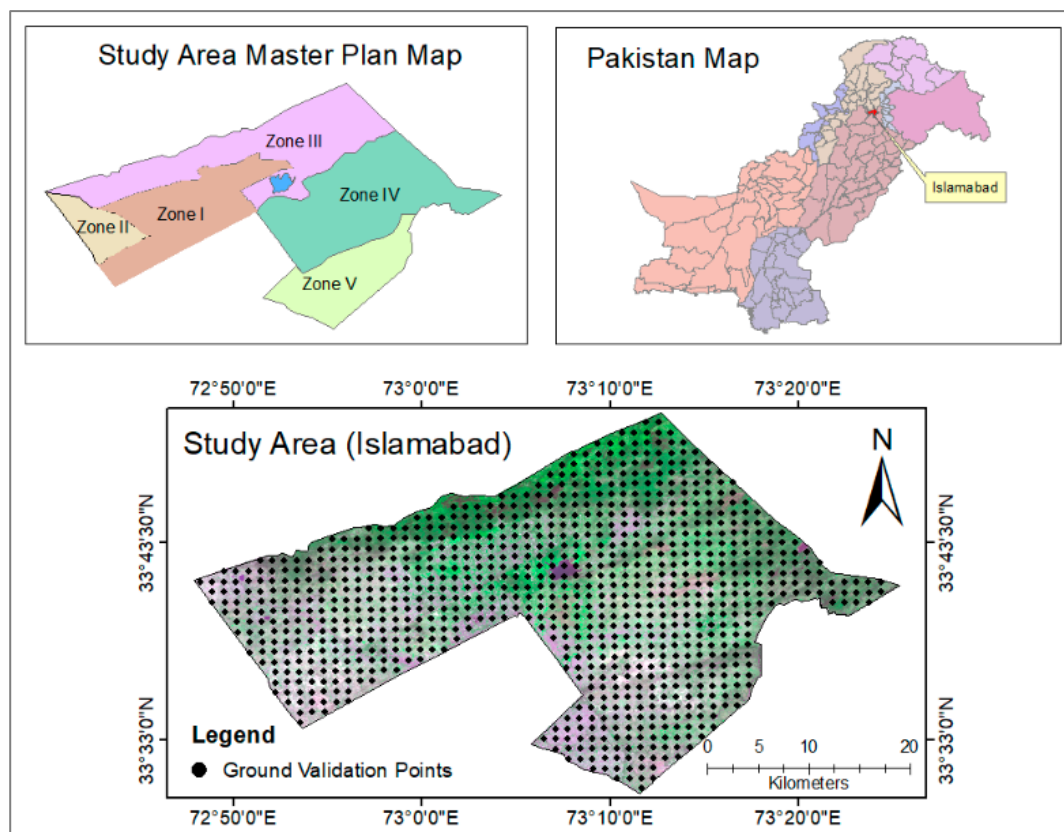


Figure 1. Geographical location of the study area of Islamabad.

2.2. Remote-Sensing (RS) Data Collection and Processing

Multispectral data of Landsat-5 Thematic Mapper (TM) and Operational Landsat Imager (OLI) Landsat-8 Enhanced Thematic Mapper (ETM) along with thermal infrared sensors (TIRS) for summers during the month of June for 1993 and 2018 were downloaded from the USGS (the United States Geological Survey) website [26]. We downloaded a single scene of Landsat, which covered the entire study area and was used for both LULC classification and LST retrieval. More details of the downloaded satellite images can be found in Table 1.

Table 1. Description of remote-sensing data.

Satellite	Spatial Resolution (m)	Cloud Cover	Date of Acquisition
Landsat-5 TM	30 × 30	0.00%	1993-06-19
TIRS	100 × 100		
Landsat-8 ETM	30 × 30	0.00%	2018-06-08
TIRS	120 × 120		

TM, Thematic Mapper; TIRS, Thermal infrared sensors; ETM, Enhanced Thematic Mapper.

All the preprocessing steps including the atmospheric correction, radiometric correction, layer stacking of different bands, and extraction of the interest area were processed before conducting image interpretation. LULC classification was classified by using the digital numbers of the spectral bands. The LST was retrieved by the Radiative Transfer Equation (RTE) method from the thermal bands of Landsat 5 and Landsat 8 (OLI), which is commonly used in previous literatures [27,28].

2.3. LST Retrieval

LST was retrieved using standard algorithms of RTE suggested by Yu et al. [29]. The RTE algorithm is based on the normalized difference vegetation index (NDVI), the proportion of vegetation (PV), and land surface emissivity (LSE). NDVI was calculated using Equation (1).

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

where *NIR* is the near-infrared band (band 5) and *RED* is the Red band (band 4 mm) in Landsat-8 OLI, while band 4 and band 3 represent the *NIR* and *RED* in Landsat-5. Band 5 (0.64–0.67 mm) and band 4 (0.85–0.88 mm) in Landsat-8 OLI are almost consistent with band 4 (0.77–0.90 mm) and band 3 (0.63–0.69 mm) in Landsat-5 and are used for the same purposes.

PV was calculated using Equation (2) based on $NDVI_{min}$ and $NDVI_{max}$ values.

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

For the LST retrieval, LSE estimation is required, which is a proportional factor that scales blackbody radiance (Planck's Law) to predict emitted radiance [30]. Equation (3) was used to calculate LSE:

$$LSE_{Bi} = Es_{Bi}(1 - Pv) + Ev_{Bi} * PV + C \quad (3)$$

where *Ev* and *Es* are the vegetation and soil emissivity values, *Bi* is the band number, and *C* represents the surface roughness (*C* = 0 for plain surfaces) taken as a constant value of 0.005. *Es* and *Ev* were taken as 0.971 and 0.987 for band 10 and as 0.977 and 0.989 for band 11, respectively [31]. To derive the brightness temperature of the thermal band at the sensor level, the LST is retrieved from Landsat TM and OLI data using an appropriate algorithm. Also, the brightness temperature from thermal bands includes the estimation of radiance from the Digital Number (DN) value. The radiance was calculated using Equation (4) developed by the National Aeronautics and Space Administration (NASA) [32] from the DN value of Landsat data.

$$Li = RADIANCEMULT_{Bi} * DN + RADIANCEADD_{Bi} \quad (4)$$

where *Li* is the sensor's spectral radiance ($m W cm^{-2} sr^{-1} \mu m^{-1}$) and *RADIANCEMULT* and *RADIANCEADD* are the band constants, available in the header file. We estimate the brightness temperature [32] from Equation (5).

$$Ts_{Bi} = \frac{K2_{Bi}}{\log\left(\left(\frac{K1_{Bi}}{Li}\right)+1\right)} - 273.15 \quad (5)$$

where *Ts* represents brightness temperature at the satellite of band *i* in kelvin and where *K1* and *K2* are constants. The method was developed by USGS (the United States Geological Survey) to compute brightness temperature. To quantify LST in Celsius from Kelvin, we subtracted 273.15 from the results [33]. Estimating LST, top of atmospheric (TOA) spectral radiance must be corrected to obtain surface spectral radiance because atmospheric effects are crucial for temperature studies [34]. In this study, we used a standard RTE suggested by Yu, Guo, and Wu [29] and expressed in Equation (6).

$$LST_{RTEBi} = EiTi + ((1 - Ei)Downwelling) + Upwelling \quad (6)$$

where *E* represents surface emissivity of the band *i*, *Ti* is a spectral radiance, and down welling and upwelling are the path radiance. For the upwelling and down welling estimations, the MOTRAN

5.0 radiative transfer code executes using 1976 standard US atmospheric profiles selecting the Urban Aerosol Model [28]. According to Planck's law, ground radiance (T_i) is expressed as follows:

$$T_i = \frac{C_1}{\text{Wavelength}_{Bi}^5 \left(\exp\left(\frac{C_2}{\text{Wavelength}_{Bi} T_s}\right) - 1 \right)} \quad (7)$$

where C_1 and C_2 are Planck's radiation constants (C_1 is $1.19104 \times 10^8 \text{ W } \mu\text{m}^4 \text{ m}^{-2} \text{ sr}^{-1}$ and C_2 is $14,387.7 \text{ } \mu\text{m k}$), wavelength represents the wavelength of bands (band 10 = 10.602 and band 11 = 12.511), and T_s is the surface temperature derived from Equation (5). The RTE method is for a single band and is, therefore, applied to both (bands 10 and 11). The results of Equation (6) for each band were put into Equation (7) to calculate mean LST. We used thermal band 6 of the Landsat-5 and thermal band 10 of the Landsat-8 OLI images due to more reliability in the estimation of LST results. Band 11 was ignored due to error in LST estimation, and the reason is the effect of water vapor absorption and sensitivity, as suggested in early studies [35].

2.4. Detection of Relative LST Change

The relative LST was derived for the years 1993 and 2018 to compare the effects of LULC on urban thermal environment. The contribution of RLST from LULC (increase/decrease) changes is derived from the mean LST of the entire study area and via each pixel value using Equation (8).

$$RLST_{ij} = LST_{ij} - LST_{i\text{mean}}, \quad (8)$$

where $RLST_{ij}$ represents the relative temperature of pixel j of class i ; LST_{ij} is the temperature of cell j of class i , and LST_i indicates the mean value of LST for urban landscape i . If $RLST_{ij} > 0$, the pixel shows positive contribution of LULC conversion, and if $RLST_{ij} < 0$, then it is a negative contribution to the thermal environment [9,14].

2.5. Preparations of Training Samples for LULC Classification Using Random Forest (RF)

Initially, different random training samples in the form of polygons were generated, representing a homogeneous area of each land-cover type in Aeronautical Reconnaissance Coverage Geographic Information System (ArcGIS) 10.6 software [36]. We created a training signature from the spectral values (digital numbers) of each band of each pixel inside each training polygon. Landsat-5 (TM) and Landsat-8 OLI (ETM) were processed in R statistical software using raster [37] and rgdal packages [38] for image processing. Furthermore, training signatures of each land-use type were extracted by training points from spectral values (digital numbers) of Landsat-5 (TM) and Landsat-8 OLI (ETM). Finally, Landsat-5 (TM) and Landsat-8 OLI (ETM) were classified into five land-cover types using an RF classification algorithm (Table 2).

Table 2. Land-cover types in the study area.

Land-Cover Classes	Description
Forest land	Subtropical broadleaves and pine forests
Impervious surface	Roads, buildings, and concrete
Grass/agriculture land	Small shrubs and cultivated land
Barren land	Bare soil/rock surfaces
Water bodies	River, open water, lakes, and ponds

RF is a supervised learning classification algorithm working with boosting and bagging ensemble methods [39,40]. This method provides high accuracy, averaging the results of several decision trees, which increases the predictive power of the model by preventing overfitting [41]. The RF classifier has been successfully used to map and classify land-cover [40,42]. Assembling learning methods (bagging and boosting) has been widely used in remote sensing, and it is a popular method

that combines K binary CART trees (classification and regression trees) [43]. Input sample subsets (sample points) used to build a tree and each tree performs a special learning algorithm that splits the inputs into subgroups. The RF trees are grown without pruning and random selection at each node, contrary to a classical decision tree method [44]. The process was repeated when maximum depth was reached or when sample numbers at the node were below the minimum sample threshold. Finally, RF labeled feature classes when each tree classified the features data during the decision phase. In our case, the sampling procedure was performed to train the supervised classifier for five different classes, as mentioned above (Table 2). Balance training samples representing each land class were taken [45]. For training data sets 7839 and 9545, training sample points were taken for 1993 and 2018, respectively. The sampling procedure was repeated 5–7 times with different sample training points to evaluate the results statistically.

2.6. Detection of LULC and Associated RLST Changes

We derived the LULC change detection map from the classified images of 1993 and 2018 and investigates the spatial changes during the two-time phases. The pixel base changes in LULC were determined and mapped by the reclassification and addition tool in ArcMap 10.6. For instance, the pixels of forest land in 1993 were reclassified as 1 and 10 in 2018. Similarly, the pixels of the build-up surface were reclassified as 2 in 1993 and as 20 in 2018. After addition of land-use/land-cover maps of 1993 and 2018, the resulted pixels were found to be either 11 (unchanged) or 12 (changing of forest land into built-up areas). More detail about the change detection methodology can be found in the previous study [46]. The change detection pixels were categorized, representing similar changes, and then converted into polygons. Finally, we investigated the RLST extracted for each polygon from the changed detection map. The warming and cooling effects of LULC changes associated with the surface temperature were investigated independently based on the total changes in the study area [47,48].

2.7. Accuracy Assessment

Classification accuracy assessment is critical to obtain reliable results and its impact on LST. Hence, a total of 929 systematic points is generated at a fixed distance of 1×1 km throughout the study area, as given in Figure 1. Among them, approximately 460 points were checked in the ground by physically visiting the forest area, agriculture area, build-up, water bodies, etc. using the global positioning system (Stonex S-7), while the remote locations are validated from high-resolution GF-2 (4 m) satellite images. User accuracy and producer accuracy are calculated for each land-cover class; the overall accuracy of classification exceeds (80%) (i.e., those for 1993 and 2018 are 84% and 91%, with Kappa coefficients of 0.79 and 0.85, respectively), which meet the requirement of the study. Finally, kappa statistics were determined from the observed and expected using the following Equation (9) [49].

$$K = (\text{observed} - \text{expected}) / 1 - \text{expected} \quad (9)$$

3. Results

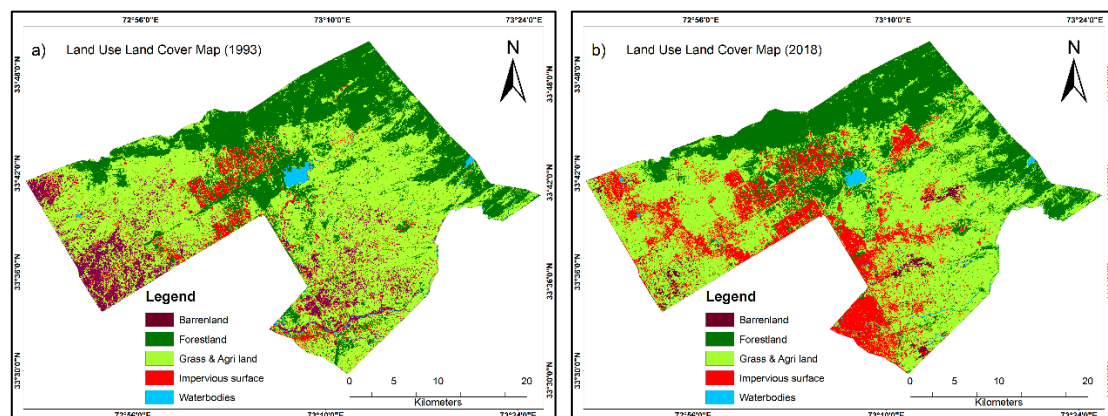
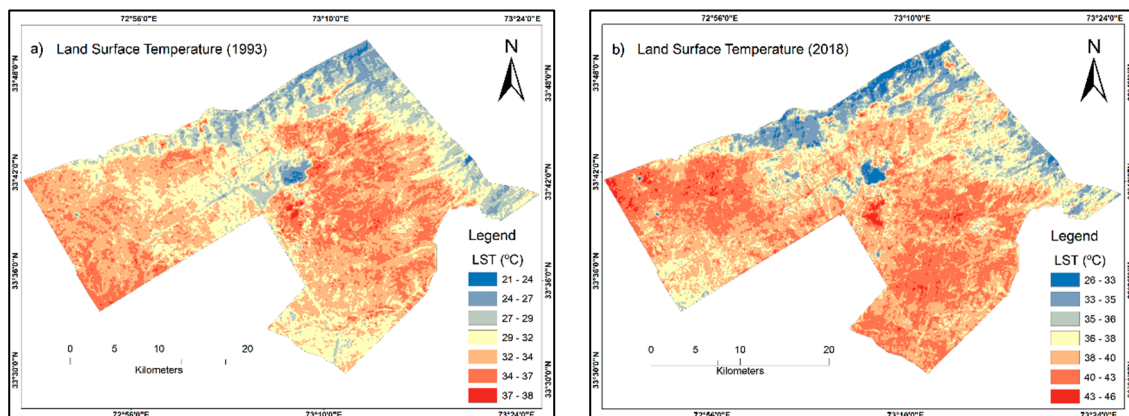
3.1. Analysis of Land-Use/Land-Cover Changes

As given in Table 3 and Figure 2, the impervious surface has increased by 11.9% at the cost of decreasing barren land (7.7%), forest land (1.4%), agriculture/grass land (2.6%), and water bodies (0.2%) from 1993 to 2018.

In general, a similar trend was found between LST and LULC changes. The minimum mean LST investigated was 21°C in 1993, while it soared up to 26°C in 2018. The highest mean LST of 1993 was 38°C , while it peaked to 46°C in 2018 (Figure 3a,b). Besides global warming and climate change, the surface temperature of the city in 1993 was low due to the abundance of green space and low percentage of impervious surfaces scattered in the core area. Due to urbanization, the minimum and maximum surface temperatures have increased in 2018.

Table 3. Comparison of land-use/land-cover (LULC) changes from 1993 to 2018.

LULC	Area (ha) 1993	Area (%)	Area (ha) 2018	Area (%)	LULC Change (ha) (1993–2018)	LULC Change (%) (1993–2018)
Forest land	27,999	29.2	26,675	27.8	1324	−1.4
Impervious surface	4327	4.5	15,703	16.4	11,376	11.9
Water bodies	966	1.0	807	0.8	159	−0.2
Barren land	9594	10.0	2193	2.3	7401	−7.7
Grass/agriculture land	53,027	55.3	50,534	52.7	2493	−2.6
Total	95,913	100	95,913	100	1324	
Overall accuracy		84		91		
Kappa coefficient		0.79		0.85		

**Figure 2.** LULC for 1993 (a) and 2018 (b).**Figure 3.** Land surface temperature (LST) for (a) 1993 and (b) 2018.

Based on the change detection map (Figure 4), about 64.74% of the urban area remains unchanged from 1993 to 2018. Overall, 35.26% of changes were observed in LULC types in the city landscape, in which 9.64% was observed in grass/agriculture land converted into impervious surfaces, followed by barren land (6.73%) into grass/agriculture, forest land (5.77%) replaced by grass/agriculture land, and grass/agriculture into forest land (5.42%) (Figure 5). A moderate change was observed in the conversion of barren land (2.39%) and forest land (1.49%) into impervious surface, the grass/agriculture land (1.34%) converted to barren land, and 1.18% of impervious surface replaced by grass/agriculture land (Figure 5). Also, a minuscule change was found in the conversion of water bodies (0.01%) into barren land, water bodies (0.07%) into impervious surface, and barren land (0.08%) into water bodies (Figure 5). The accelerated anthropogenic activities significantly replaced the natural surface into seminatural or impervious surfaces and other land-use types from 1993 to 2018. (Table 3).

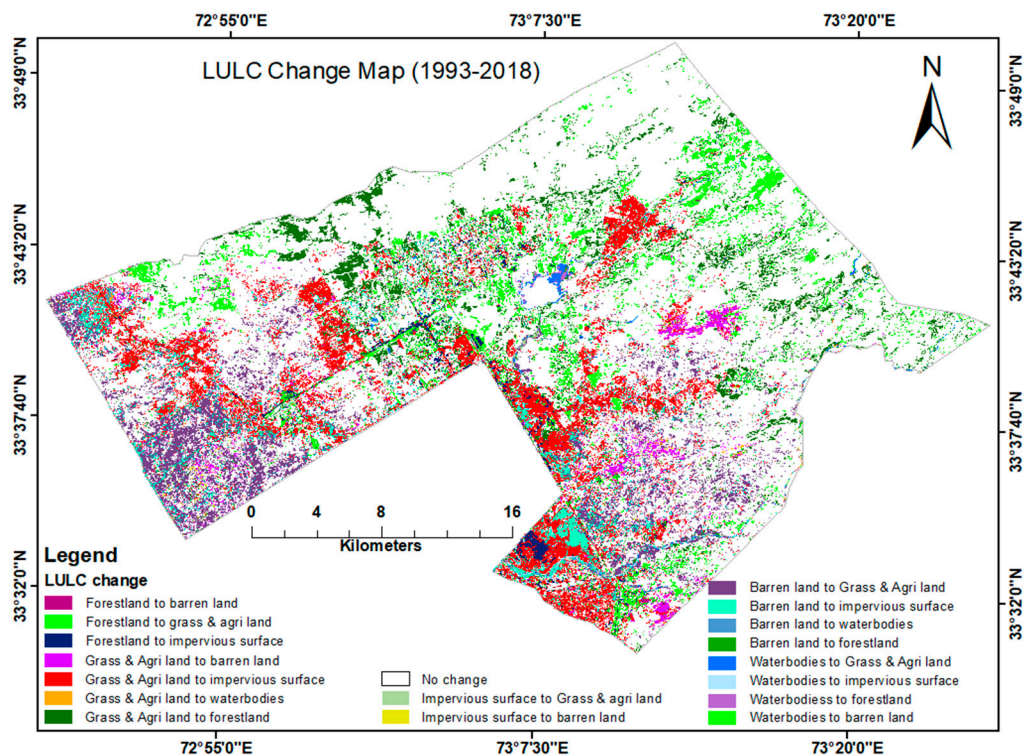


Figure 4. LULC change detection from 1993 to 2018.

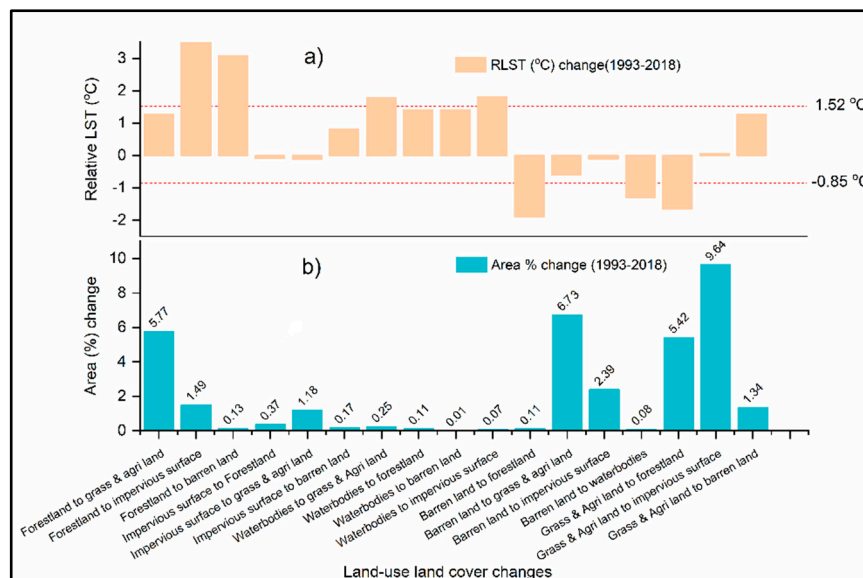


Figure 5. LULC and RLST changes from 1993 to 2018: (a) change in RLST °C and (b) change in % of LULC area.

3.2. Warming and Cooling Effects of Land-Use Conversion from 1993 to 2018

As given in Figures 5 and 6, the LULC changes had warming and cooling impacts on urban climate. The overall maximum warming effects of 3.78 °C and 3.09 °C were observed in the impervious surfaces and in barren land transformed from forest land. The continued urbanization replaced the water bodies by impervious surface and grass/agriculture land, which has increased the RLST by 1.81 °C and 1.78 °C, respectively. The moderate warming effects of 1.41 °C and 1.42 °C were quantified in the transformation of water bodies to forest land and barren land. The minimum positive effect

on surface temperature was noticed in the conversion of impervious surfaces to barren land and grass/agriculture land to impervious surfaces.

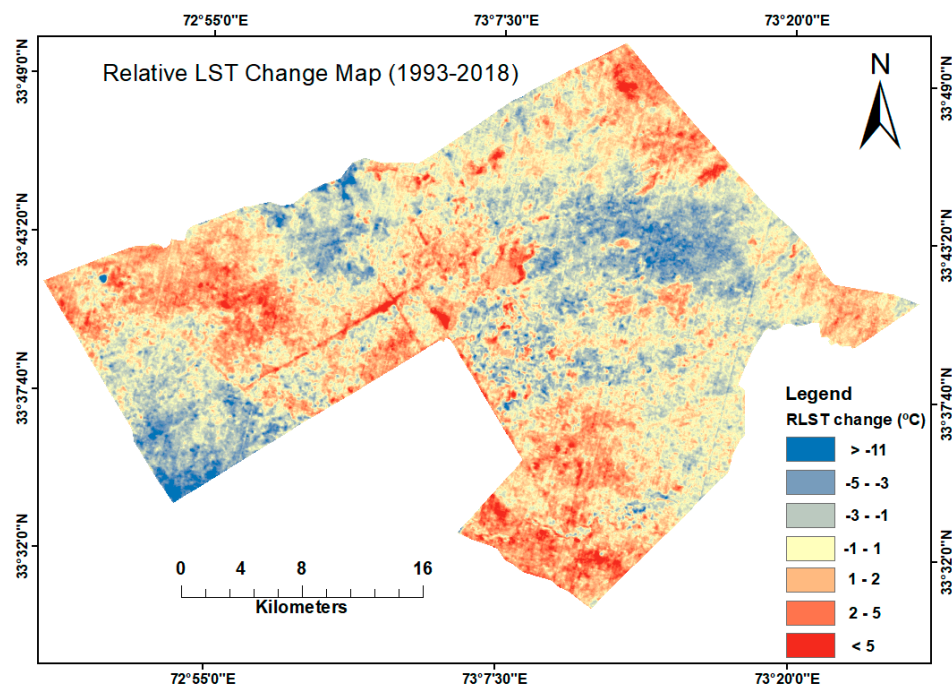


Figure 6. Relative LST (RLST) change from 1993 to 2018.

On the other hand, the maximum cooling effects of about $-1.90\text{ }^{\circ}\text{C}$, and $-1.65\text{ }^{\circ}\text{C}$ were observed in the conversion of barren and grass/agriculture land into forest land. A moderate decline in surface temperature of about $-1.32\text{ }^{\circ}\text{C}$ was quantified in the water bodies transformed from barren land. The minimum cooling contribution of $-0.1\text{ }^{\circ}\text{C}$ was observed in the conversion of impervious surfaces to grass/agriculture land due to the minimum difference in surface energy in grass/agriculture land and impervious surface. The conversion of barren land into grass/agriculture land and impervious surfaces had cooling effects of $-0.11\text{ }^{\circ}\text{C}$ and $-0.61\text{ }^{\circ}\text{C}$ (Table 4). More details about the spatial locations of each LULC changes and its impact on RLST are given in Figures 5 and 6. The significant positive effect on RLST is linked to the conversion of forest land into barren land and impervious surfaces, while the cooling effect is associated with the conversion of barren land and grass/agriculture land into forest land. We also investigated moderate changes in surface temperature in the water bodies and grass/agriculture land converted into barren land and impervious surfaces. Overall, in the land-use conversion in the city landscape, the average warming contribution of land-use types had increased the surface temperature by $1.52\text{ }^{\circ}\text{C}$, while the average cooling effect was $-0.86\text{ }^{\circ}\text{C}$, estimated in the entire study area over the last 26 years. The different cooling effects with respect to LULC changes are related to surface physical characteristics, evapotranspiration, and the conversion area of each land-use type.

3.3. Contribution of Land-Use/Land-Cover Conversion to UHI

The study investigated the impact magnitude of LULC conversion and its contribution to UHI intensity from 1993 to 2018. The contribution of land-use types to UHI was quantified based on the average warming and cooling values using a standardized scale of 10%. Based on the standard scale of LULC transformation and UHI (10%), the positive contribution to UHI was observed higher in the conversion of natural surface into impervious surfaces compared to the cooling effect of LULC types in the back direction. Our results showed maximum positive supplement of 1.19% in UHI in the transformation of forest land into impervious surfaces, while the negative contribution of -0.2% was observed in the reverse changes. The conversion of forest land into grass/agriculture and barren

land had warming contributions of 0.40% and 0.97% and cooling contributions of −1.5% and −1.7% in the conversion in the back direction, respectively. The grass/agriculture land transformed into impervious surface had a warming contribution of 0.02% and cooling contribution of −0.10% to UHI due to transformation in the reverse changes. The supplement of 0.25% to UHI was observed due to the alteration of impervious surface into barren land, while the negative addition of −0.10% to UHI was found in the conversion of barren land into impervious surface. In addition, the positive and negative contributions of 0.40% and −0.5% were found in the interconversion of grass/agriculture land to barren land. The positive effect was due to the conversion of natural surface into impervious surfaces, which had maximum contribution to UHI compared to the cooling effect in the reverse change. The details of each land-use conversion and their contribution to UHI are depicted in Tables 5 and 6.

Table 4. Summary of LULC, RLST (°C) changes, and impact (+, −) during the period 1993–2018.

LULC Conversion	Area (ha)	Area (%)	Min LST (°C)	Max LST (°C)	Mean LST (°C)	Impact (+/−)
Forest land to barren land	123.8	0.13	−2.1	8.9	3.09	+
Forest land to impervious surface	1430.8	1.49	−4.05	11.59	3.78	+
Water bodies to impervious surface	70.9	0.07	−3.4	6.8	1.81	+
Water bodies to grass/agriculture land	238.6	0.25	−4.5	7.5	1.78	+
Water bodies to barren land	10.5	0.01	−2.9	5.6	1.42	+
Water bodies to forest land	106.3	0.11	−4.2	6.9	1.41	+
Grass/agriculture land to barren land	1286.9	1.34	−8.6	7.4	1.28	+
Forest land to grass/agriculture land	5536.1	5.77	−6.1	8.9	1.27	+
Impervious surface to barren land	164.5	0.17	−12.7	12.1	0.81	+
Grass/agriculture to impervious surface	9241.3	9.64	−7.9	8.1	0.07	+
No change	62,091.9	64.74	−9.2	9.2	0.00	
Barren land to impervious surface	2291.9	2.39	−7.8	6.0	−0.11	−
Impervious surface to grass/agriculture land	1129.6	1.18	−7.8	6.7	−0.11	−
Impervious surface to forest land	351.7	0.37	−6.1	4.2	−0.26	−
Barren land to grass/agriculture land	6451.7	6.73	−8.8	7.2	−0.61	−
Barren land to water bodies	74.61	0.08	−10.6	5.4	−1.32	−
Grass/agriculture land to forest land	5202.1	5.42	−9.5	7.4	−1.65	−
Barren land to forest land	109.71	0.11	−7.2	3.6	−1.90	−
	95,912.92	100				

Table 5. The LULC change warming effect, percentage contribution in surface temperature, and standardized percentage contribution (10%) of LULC types.

LULC Loss	Area Change (ha)	Area (10%)	RLST (°C)	RLST ¹ (10%)	(UHI) ² (10%)
Grass/agriculture land to impervious surface	9241.3	5.07	0.07	0.04	0.02
Impervious surface to barren land	164.5	0.09	0.81	0.48	0.25
Forest land to grass/agriculture land	5536.1	3.04	1.27	0.76	0.40
Grass/agriculture land to barren land	1286.9	0.71	1.28	0.77	0.40
Water bodies to forest land	106.3	0.06	1.41	0.84	0.44
Water bodies to barren land	10.5	0.01	1.42	0.85	0.45
Water bodies to grass/agriculture land	238.5	0.13	1.78	1.06	0.56
Water bodies to impervious surface	70.9	0.04	1.81	1.08	0.57
Forest land to impervious surface	1430.8	0.79	3.78	2.26	1.19
Forest land to barren land	123.8	0.07	3.09	1.85	0.97
Total	18209.7	10.00	1.52	10.00	

Note: (1) Relative land surface temperature (RLST) (10%) is obtained from converting RLST (°C) values into 100% and then derived 10%, and (2) Urban heat island (UHI) was derived from the division of cooling (0.8 °C) and warming (1.52 °C) values and by multiplying to the values of RLST of each class.

Table 6. The LULC changes cooling effect, percentage rise in surface temperature, and standardized percentage contribution (10%) to urban heat island (UHI).

LULC Gain	Area Change (ha)	Area (10%)	RLST (°C)	RLST ¹ (10%)	UHI ² (10%)
Barren land to water bodies	74.61	0.05	−1.32	2.2	−1.16
Barren land to forest land	109.71	0.07	−1.9	3.2	−1.68
Impervious surface to forest land	351.7	0.23	−0.26	0.4	−0.23
Impervious surface to grass/agriculture land	1129.6	0.72	−0.115	0.2	−0.10
Barren land to impervious surface	2291.9	1.47	−0.11	0.2	−0.10
Grass/agriculture land to forest land	5202.1	3.33	−1.65	2.8	−1.46
Barren land to grass/agriculture land	6451.7	4.13	−0.61	1.0	−0.54
Total	15611.32	10.00	−0.85	10.0	

Note: (1) RLST (10%) is obtained from converting RLST (°C) values into 100% and then derived 10%, and (2) UHI was derived from the division of cooling (0.85 °C) and warming (1.52 °C) values and by multiplying to the values of RLST of each class.

4. Discussion

4.1. Impact of Land-Use/Land-Cover Changes

Under the master plan, Islamabad is designed as a linear city arranged in straight sectors and intersecting roads. Unlike other cities, the city planned to comprise of 220.15 km² of built-up area, rural area of 460.20 km², and 220.15 km² of green space and parks. Each residential sector is identified by a letter of the alphabet and by a number and covers an area of approximately 2 × 2 km². It means that the city is built for the present and planned for the future as well. However, due to urbanization, the city landscape is changed with LULC changes and affected the city thermal environment during the period 1993 to 2018. We found that the forest land is decreased annually by 0.056% at the cost of increasing impervious surfaces due to deforestation and forest degradation during the 25-year period from 1993 to 2018. The rate of decline of the green space is less than the current annual average estimated values of 0.6% [1], 0.54% [20], and 0.7% (1990 to 2010) [50] in the northern part of Pakistan. It means that the urban forest of Islamabad is protected compared to the remote areas of the country where the annual deforestation rate is high. Also, in contrast to our results, recently, Gilani et al. [51] reported that annual canopy decreased by the rates of 0.81% and 0.77% for tree cover >40% and <40%, respectively, during 1976 to 2016 in the city of Islamabad. Based on results derived from the LULC change map, the forest cover is replaced by grass/agriculture land, impervious surfaces, barren land, and water bodies due to expanded anthropogenic activities. The expansion of impervious surface mainly occurred in the northeast and northsouth directions in the city. Such LULC changes bring differences in surface energy and impacted relative surface temperature. For instance, the conversion of forest land into impervious surfaces has increased the surface temperature due to the transformation of high to low evaporative surfaces. The conversion of forest land into water bodies contributed little in RLST and is almost negligible, which could be because of the edging effect and the small area being converted. In a study similar to our findings, Fu and Weng [8] investigated the most considerable annual LST difference by 5.7 K in the converted vegetated area to built-up areas from multi-satellite images from 1984 to 2011. Recently, Wang, Hu, Myint, Feng, Chow, and Passy [7] also concluded that the conversion of vegetation to built-up area had significant influence on the increase of LST. Comparing to the abovementioned studies, it is evidenced that reducing forest area with consequent increases in impervious surfaces and barren lands can increase surface temperature in the urban area.

Furthermore, like the expansion in impervious surfaces at the cost of declining other land-cover types (Table 3), a similar trend of urban expansion has been reported in major cities of Pakistan. For instance, Saleemi [52] conducted a study in Lahore and found a significant expansion of 20% due to urbanization. Also, Raziq, Xu, Li, and Zhao [19] found 26.59% increasing rate in urbanization in the city of Peshawar from 1999 to 2016. The study of Mahboob, Atif, and Iqbal [18] reported increased urban patterns from 486 to 729.2 km² during the period 1991 to 2000, and from 2000 to 2013, the

urban growth has increased by 1582.5 km² in the metropolis of Karachi. In summary, with the LULC changes in the urban area bring changes in the surface temperature, which contributed to the urban thermal environment.

4.2. Warming and Cooling Effects of Land-Use Conversion and Its Implication for Sustainable Future Cities

In heterogeneous urban landscapes, the alteration of land-use/land-cover brings warming and cooling effects, particularly, the transformation of natural surface to anthropic surface and vice versa. In this study, the conversion of forest land into impervious surfaces significantly contributed to relative LST because of the conversion of high (forest land) to low (impervious surface) evaporative surfaces. Green plants absorb more water through roots and transpire into the atmosphere on hot summer days, which increase the humidity and co-benefited the surrounding urban area. The significant warming effect in the city is due to the transformation of water bodies, forest land, and agriculture land into barren land and impervious surfaces. The moderate warming effect is observed in the land-use conversion from forest land into grass/agriculture land and from water bodies into other land-use types. This is due to the conversion in small fragmented parcels that may be affected by the edging effect. Such an effect was observed in the surrounding area of a big water lake (Rawal Dam) which suppresses the surrounding surface temperature of the man-made structures. The minimum warming effect is noticeable in the conversion of agriculture to impervious surfaces and of impervious surfaces to barren land, which often appears as small roads/a footpath on the banks of the water body. For instance, in the surrounding area of Rawal Lake (8.8 Km²), maximum cooling was observed in the city of Islamabad, while in the large forest patches of 600 ha of the Shakarparian forest is observed a cooling effect in the surrounding environment. The riparian zone of the lakes is converted into impervious surfaces by constructing recreation spots, viewpoints, and embankments where the changes in the RLST are almost negligible in proximity. The findings of our study reveal that the transformed land-use types may have minimal effects on surface temperature due to large neighboring water bodies or green spaces. Overall, in the LULC conversion, the average warming effect is 1.52 °C, which is due to the conversion of high to low evaporative surfaces that supplemented the urban thermal environment during 1993 to 2018. It means that the warming effect is much higher and comparable to Khan and Fee [53], who investigated the increase of temperature of 0.7 °C between 1961–2014, predicted to be 2.2 °C based on the grid data in 2090. A study of Kayet et al. [54] reported high LST with the consequent increase in the built-up area from 1994 to 2014. Similarly, the study of Xu et al. [55] concluded that the contribution of impervious surfaces to regional LST could be six times higher than the sum of vegetation and water bodies during 1989–2009. A recent study by Zullo et al. [56] demonstrated that the increased built-up area by 630 km² in Italy has elevated mean surface temperature of 1.36 °C and concluded that the expansion in the built-up area can enhance the LST/RLST in urban climate. Our study investigated higher surface temperature in the impervious surface similar to the above mentioned studies but contradictory to the study of Sun and Chen [14], who reported higher LST in the barren land while similar to the highlighted hot and cold spots based on the RLST in the city of Beijing. Our findings of higher relative LST in impervious surfaces and low RLST in water bodies are confirmed by the study of Naeem et al. [24]. Likewise, a more recent study by Yu, Yao, Yang, Wang, and Vejre [9] investigated the impacts of the land-use changes on RLST in the agglomeration regions of China, which are in substantial agreement to our results. This study shows higher RLST in the impervious surface, soaring up surface temperature in the core city (Table 4).

In the urban area, the green space and impervious surfaces are crucial elements affecting urban climate. Few samples were highlighted as an evidence of LULC changes that has shown great impact on surface temperature during 1993 and 2018 in the city of Islamabad. For instance, in the city, the forested area is transformed into impervious surface, and the RLST is increased greatly by 3 to 9 °C, while it is decreased by −1 to −3 °C in forest land transformed from impervious surface (Figure 7a–d). Urban landscape managers and planners exercise different landscape practices which affect the RLST. As a result, the RLST will be increased or decreased in the land-use conversion. The warming effect

compared to the cooling is often much higher due to replacement of large areas of natural surface into seminatural or artificial surfaces. The difference in RLST values is clear and visible in the change detection map (Figure 5). Overall, the impervious surface being transformed from natural surface contributed much to RLST value. Our results of higher values of RLST in the impervious surface converted from green space are in agreement with recent findings of the study [9].

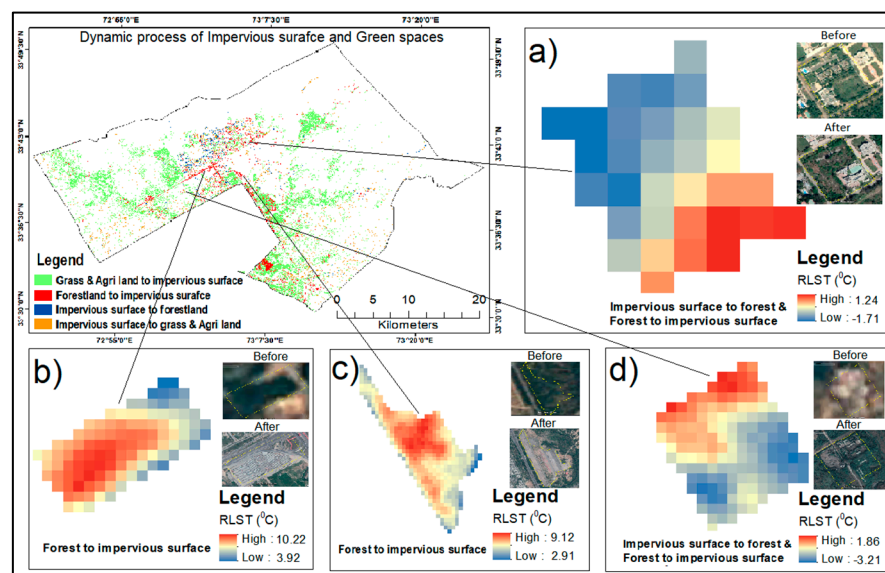


Figure 7. LULC change contribution in LST from 1993 to 2018: (a,d) interconversion of forest and impervious surfaces and (b,c) forest land to impervious surfaces.

4.3. Land-Use Conversion and Their Contribution to UHI

The land-use/land-cover changes and associated RLST demonstrates the positive and negative contributions in the urban climate at the standardized scale (10%). For instance, the study demonstrates that the transformation of forest land into barren land contributes 1% to UHI, while the cooling effect is -1.7% in the reverse direction of the same area (0.67%) conversion, which is higher than the warming effect. The reasons for such surprising findings may be the locations of the LULC changes close to water bodies and forest land. On the other hand, the conversion of same area (0.3%) of forest land into grass/agriculture contribute a warming effect of 0.4% and a cooling contribution of -1.46% to UHI in the converse transformation. Similarly, the conversion of forest land into impervious surfaces contributes about 1.2% to UHI, while the negative contribution is -0.2% in reverse change; the warming contribution is maximum, larger than the cooling contribution due to the transformation of low to high heat surface energy. It is clear from the findings that the warming contribution is much higher than the cooling contribution when the natural surface is converted into the impervious surface. Overall, the study demonstrates that the maximum warming contribution is due to the transformation of green space; particularly, the urban forest to impervious surface increased the surface temperature, while the minimum effect is due to the conversion of grass/agriculture to impervious surface, which has minimum difference in surface temperature. It reveals that increasing green space in the urban area can co-benefit the urban climate while the barren land and impervious surfaces have low heat transfer capacity and trapped solar energy that can boost the urban thermal climate. The study of Gogoi, Vinoj, Swain, Roberts, Dash, and Tripathy [47] concluded the overall contribution of 25%–50% warming associated to LULC changes and matches well with the estimated warming due to physical association over the Indian region, which confirms our results.

Indeed, in the land-use dynamic process, the maximum warming contribution is 1.2% in the conversion of forest land into impervious surface, while the minimum warming of 0.02% is observed from the change of grass/agriculture land to impervious surfaces. The reason for minimum contribution

of grass/agriculture land is due to the minimum difference in surface temperature and proximity to impervious surface. Meanwhile, the maximum cooling is investigated in the conversion of barren land to forest land, while the minimum is obtained from the transformation of barren land to grass/agriculture land. The cooling contribution of some land-use types are converted back into forest land, water bodies, and grass/agriculture land. Similarly, the study of Hu, Zhou, and He [48] concluded the effect of land-use/land-cover changes on surface temperature and the percent contribution in surface temperature related to LULC changes in Dongting Lake Area, China, with the results in accordance to our findings. Due to limited literature on LULC changes, associated RLST, and their percent contribution, proper comparison is a bit difficult.

5. Conclusions

The LST associated with LULC changes has been a well-known phenomenon across the world. Investigating LULC changes using temporal Landsat images over the last 25 years, this study found significant expansion of impervious surface (11.9%) at the cost of a decline in other land-use types. Overall, the findings demonstrate the average warming effect of 1.52 °C and the average cooling effect of −0.8 °C of LULC changes in the city of Islamabad from 1993 to 2018. It reveals that the warming effect of the impervious surface transformed from the natural surface is higher compared to the cooling effect due to a higher rate of conversion of natural surfaces to impervious surfaces as compared to impervious surfaces to natural surfaces. Moreover, based on the standardized scale of LULC changes (10%), the average warming contribution of land-use/land-cover changes to UHI is 1.2% due to the transformation of forest land to the impervious surface.

In comparison, the cooling contribution of −0.2% is observed in changes in the backward direction. The positive contribution in UHI due to the conversion of forest land into the impervious surface is higher than the negative contribution. The UHI intensity is mainly associated with the biophysical properties of the surface (heat transfer capacity and evapotranspiration), which brings changes in the RLST. However, the LULC-induced warming has risen over this region, which has plenty of green space. The study indicates that more comprehensive investigations are instantly mandatory to know land-use/land-cover and associated surface temperature changes to local and regional climate. Due to the consequences of progressive activities, numerous regions are enduring a speedy revolution as a result of intensifying the effects of current climate change. Hence, there is a greater need for green policy intervention and effective urban planning to control the soaring thermal environment. The study suggests intensive research in the future, specifically to investigate the proportion of green space and impervious surface and its impact on RLST for sustainable future cities.

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