The Response of Land Surface Temperature to the Changing Land-Use Land-Cover in a Mountainous Landscape under the Influence of Urbanization: Gilgit City as a case study in the Hindu Kush Himalayan Region of Pakistan

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Abstract: With growing urbanization in mountainous landscapes, the built-up areas dominate other land use classes resulting in increased land surface temperature (LST). Gilgit city in northern Pakistan has witnessed tremendous urban growth in the recent past decades. It is anticipated that this growth will exponentially increase in the near future because of the China-Pakistan Economic Corridor (CPEC) initiatives, as this city happens to be the commercial hub of the northern region of Pakistan. The objective of present study is to explore the influence of land use and land cover variations on LST and to evaluate the relationship between LST with normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and normalized difference builtup index (NDBI) values. This study is carried out on data from Google earth and three Landsat images (Landsat 5-TM, Landsat 7-ETM, and Landsat OLI TIRS-8) during the period from 1992, 2004 and 2016. Land use/cover classes are determined through supervised classification and LST maps are created using the Mono-window algorithm. The accuracy assessment of land use/cover classes is carried out comparing Google Earth digitized vector for the periods of 2004 and 2016 with Landsat classified images. Further, NDVI, NDBI, and NDWI maps are computed from images for years 1992, 2004, and 2016. The relationships of LST with NDVI, NDBI, and NDWI are computed using Linear Regression analysis. The results reveal that the variations in land use and land cover play a substantial role in LST variability. The maximum temperatures are connected with built-up areas and barren land, ranging from 48.4°C, 50.7°C, 51.6°C, in 1992, 2004, and 2016, respectively. Inversely, minimum temperatures are linked to forests and water bodies, ranging from 15.1°C, 16°C, 21.6°C, in 1992, 2004, and 2016 respectively. This paper also results that NDBI correlates positively with high temperatures, whereas NDVI and NDWI associate negatively with lesser temperatures. The study will support to policymakers and urban planners to strategize the initiatives for eco-friendly and climate-resilient urban development in fragile mountainous landscapes.

Keywords: Land surface temperature, land use land change, Gilgit, HKH.

Introduction

In recent decades, researchers and policymakers greatly focus to understand rapidly changing climatic conditions and associated impacts under the activities. influence of human The rapid industrialization and urbanization processes have a major contribution towards global climate change and one of the concerns in this process is rising surface temperatures in urban areas due to land use and land cover change (LULC). Recent research showed that land use and land cover change contribute 68% of the warming trends (Zhou et al., 2004) and substantial effects on the regional climate change (Hale and Loveland, 2008; Kalnay and Zhou, 2005; Lim and Cai, 2005, Laux et al., 2017). The change of land surface into built-up areas comprising housing and commercial infrastructure i.e., road networks, etc. affects temperature, air quality and relative humidity (Zhao et al 2004, Tran et al., 2017, Trotter et al., 2017). Loss of vegetative cover by

replacing with built-up infrastructure cause urban heat island (UHI), a term commonly used to describe the higher temperature in an urban area as compared to rural settings. Such a situation has adverse effects on the lives and daily activities of urban population (Santamouris, 2015, Lee et al., 2017) and it causes more concern because one quarter of the mountain areas and half of world's inhabitants live in cities. In addition. UHI greatly influences the upper atmosphere with increasing warming trends and the greenhouse effect (Kalnay and Cai, 2003; Zhong et al., 2017). UHI is influenced by many factors that include LULC. The analysis of land use/change due to urbanization shows that it has a high influence on UHI intensity (He et al., 2007; Singh et al., 2017; Arsiso et al., 2018). Considering IPCC Fifth Assessment Report (IPCC 2013b), since 1880 worldwide mean surface temperatures have increased by 0.84 C and recent studies have projected 0.27 C mean surface warming per century is due to land-use changes alone (Kalnay and Cai, 2003; Mahowald et al., 2017). Thus, it is imperative to analyze LULC particularly for those regions that are more vulnerable to climate change effects. Any adverse effect on such regions can make the life of the huge population and its habitat very challenging. For example, the Hindu Kush Karakoram Himalayan (HKH) region covers more than 4.3 million km^2 area, in eight countries including Afghanistan, Pakistan, China, India, Nepal, Bhutan, Bangladesh, and Myanmar. It also encompasses several highest peaks and provides water and ecosystem services to ten large rivers basins in Asia, consequently 1.3 billion people are dependent on the water of these rivers' basins (Singh et al., 2011). The warming trends in such regions like HKH which are predicted to rise by 4-5°C and increase in rainfall by 20-40% are perturbing due to potential hydrological variations that can affect water availability and ecosystem services for huge populations relying on glaciers (Barnett et al., 2005; Kulkarni et al., 2013). The warming trend on the HKH is apparent causing glacier retreat, reduction in snow cover change, rise in surface temperature (Barnett et al., 2005; Pepin et al., 2015; Qiu, 2008; Mukhopadhyay, 2015; You et al., 2017, Wu et al., 2017; Ren et al., 2017). The ten large river basins in the HKH where snow and glacier mostly contribute to river discharge are very receptive to climate change (Kumar et al., 2015). The HKH is apparently one of the most sensitive regions for climate change. Many studies and models are used to determine the past, current and future warming trend in the face of global warming. However, highly limited climatic related data of the region restricts proper cross-validation of the many climate change conclusions in the region, making imperative to make more efforts for international, national and local bodies for the availability of valid data (IPCC 2013a, 2013b).

This research study will also help to understand dynamics of urbanization in fragile mountainous landscape and its potential as a contributing factor in changing local climate conditions. In addition, to support capacity building of local mountain communities to formulate policies to cope with climate change factor. More specifically the research aims at studying the impact of LULC on land surface temperature to determine relationship between LST and land usage types.

Materials and Methods

Study Area

The study was conducted in Gilgit city, the capital of Gilgit-Baltistan (G-B), in northern Pakistan. It lies between $35^{\circ}51'31.99''$ N to $35^{\circ}55'58.18''$ N and $74^{\circ}13'27.39''$ E to $74^{\circ}31'24.15''$ E, at 1500 m altitude (Fig. 1). The study area was selected because of its current unprecedented urban growth and its strategic location, considered as the gateway to the CPEC and Karakoram Highway, a junction between China and

Eurasian countries. In addition, the area is located in high climate change vulnerability region of HKH.

The city is surrounded by high altitude barren and snow-covered mountains. Gilgit experiences an extreme climate, in winter temperature goes down to minus degree Celsius and in summer, it rises to 40 degrees Celsius with bright sunshine. Gilgit lacks substantial rainfall, averaging in 134 mm annually (Adnan et al., 2017). Urbanization and vegetation make the major land use of the study area. Urban areas mainly comprise of residential units, commercial areas, public buildings, roads, and educational facilities. Agricultural activities include the fruit orchards, agroforestry, and cultivation of wheat and potato. Snow and glacial melts, gravity-fed water from streams and water pumping from Gilgit river using thermal or hydroelectricity are the main sources of irrigation in Gilgit city.



Fig. 1 Study area.

Data Collection

The study is based on primary and secondary sources, which is collection and analysis of remote sensed and GIS-based data ensuring the high accuracy in determining the change in land use/cover with corresponding variations in land surface temperature (LST). A time-series of Landsat images were used which include Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI) images to develop land use/ cover maps that included full scenes for the study area for the years 1992, 2004, and 2016, respectively. All bands including the thermal bands, which are common for determining LST, were used in this study. The images were cloud-free (less than 1%) acquired in July, *i.e.* summer time while vegetation growth is at its peak. The primary dataset is downloaded from the archives of the United State Geological Survey (USGS) with 30-meter spatial resolution. Whereas, secondary data that include district and municipal boundaries were sourced from the government of

Gilgit-Baltistan. Google Earth (GE) was also used in this study to download two images from Google Earth 5.0. in August 2004 and August 2016 having green, Computation of NDVI, NDWI, and NDBI; (4) LST for each image is computed; (5) Data were analyzed, calculated, and manipulated through attribute tables



Fig. 2 Details of land use land cover change.

Table 3. Details of land-use change.

Land use types (Class name)	Area (Hectares) 1992	Area Percentage 1992	Area (Hectares) 2004	Area Percentage 2004	Area (Hectares) 2016	Area Percentage 2016	Area Changed (Hectares)
Built-up Land	139.1	3.3	174.3	4.1	538.2	12.7	399.1 (Increased)
Water	237.1	5.6	230.2	5.5	216.1	5.1	21 (Decreased)
Vegetation Land	1054.2	25.0	949.5	22.5	926.7	21.9	127.5(Decreased)
Agriculture Land	701.5	16.6	998.3	23.6	879.5	20.8	178 (Increased)
Barren Land	1916.3	45.4	1870	44.3	1487.4	35.2	428.9(Decreased)

red, and blue bands with a spatial resolution of 2 meters. Detailed description of the data used for this study is given in Table 1.

Table 1 Description of data used for this study.

Data Type	Data production	Scale (m)	source
Landsat TM	July 1992	30	USGS
Landsat ETM	July 2004	30	USGS
Landsat OLI/TIRS	July 2016	30	USGS
Google Earth Images	August 2004	2	Google Earth
Google Earth Images	August 2016	2	Google Earth
DEM		30	USGS
SRTM		30	USGS
Administrative boundary			

Landsat images were analyzed through different steps: (1) Image pre-processing and image enhancement; (2) Image classification; (3) in ArcGIS after being converted to vector files (Fig. 2).

Image Pre-Processing and Enhancement

The study was mainly based on the collection and analysis of remotely sensed data. The images were cloud-free acquired in July. The dataset was mainly downloaded from the archive of the United State Geological Survey (USGS). Three cloud-free Landsat images of the year 1992, 2004 and 2016 were rectified to UTM 43 Zone. Image processing was performed in ILWIS 3.6 Software, like filtering, image equalization, histogram equalization, band composition, and starching.

Keeping in view the increasing trend of using Google earth derived imagery by different commercial companies and researchers through visual interpretation to complement low-resolution multispectral digital data. Thus, this study also used Google earth derived images by manually digitalizing to complement Landsat dataset using five classes that include vegetation, agriculture land, built-up land, water bodies and barren land. Google Earth (GE) 5.0 was used to download two GE images. These GE images acquired on 13 August 2004 and August 2016 and have green, red, and blue bands with a spatial resolution of 2 m. Both images were georeferenced by using UTM 43 coordinate system in ArcGIS software; geo-referenced images were later mosaicked in ArcGIS software.

Image Classification

Landsat images for the benchmarks 1992, 2004 and 2016 were mapped for five LULC types namely; vegetation land, agriculture land, built-up areas, water bodies, and barren land were focused for this study. Training sites were developed after analyzing ancillary information, spectral and spatial profiles, as well as reference data from several sources. For individual land cover class 40 pixel of 40 training samples were selected. After training sites were digitalized, their statistical properties of land cover categories were computed. The maximum likelihood algorithm was used for the classification of Landsat images with a supervised signature extraction. The accuracy assessment was carried out on three classified maps using stratified random sampling methods. Total 40 samples were chosen from each LULC class to verify with field check and field survey data were used as reference data for accuracy assessment. The accuracy of classification was 86%, 83%, and 88% with a Kappa coefficient of 0.62, 0.69, and 0.72, respectively for the years 1992, 2004, and 2016 respectively (Table 2).

Years	Overall Accuracy	Kappa Index
1992	86%	0.75324
2004	83%	0.75791
2016	88%	0.75549

Table 2. Accuracy assessment for the years 1992, 2004 and 2016.

Computation of NDVI, NDWI, and NDBI

Several studies have used NDVI parameter to detect and monitor land LULC changes (Lunetta et al., 2006; DeFries and Townshend, 1994; Bery and Mackey, 2018; Zoungrana et al., 2018) as a comparison with other indices it is less sensitive to atmospheric conditions. In this study, NDVI was used to analyze and represent the relationship between vegetation area and LST by linear regression correlation. Following formula was used to compute NDVI for an image:

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

NDBI is used by several researchers for monitoring built-up and human settlements situations (Xu 2007; Guha et al 2018; Jianhui et al 2018). NDWI is determined to indicate the state of water state of vegetation (Mcfeeters, 1996). The values can be in the range of -1 to +1 for NDWI and NDBI. Positive values represent more water bodies, built-up and vice-versa for negative values (Gao, 1996). The formula for the computation of these indices are as follows:

$$NDBI = \frac{MIR - NIR}{MIR + NIR} - \dots - (2)$$
$$NDWI = \frac{NIR - MIR}{NIR + MIR} - \dots - (3)$$

Computation of Land Surface Temperature

$$TB = \frac{k2}{\ln\frac{k1}{R} + 1} - \dots - (5)$$

Where

Tb=is the satellite brightness temperature is degree kelvin

 K_1 = 666.09- is the constant used for the study area

K₂=1282.71-is the constant used the study area

The three LST images derived were then converted to the most common unit-degrees Celsius-by subtracting with absolute zero (approximately -273.15 c) using the raster calculator.

Results and Discussion

The results of this research are presented in the following three subsections.

Land Use/Land Cover Maps

By using supervised classification maximum likelihood method, the Landsat imagery of each composed image for the years 1992, 2004, 2016 were classified into five area classes namely vegetation, agriculture, built-up areas, water bodies, and barren land with high accuracy, covering an area of approximately 4222.2 hectares (Table 3, Fig. 2). LST variations were caused by LULC, particularly around the main city areas, which have increased drastically.

The results (Table 3 and fig. 3) reveal that there is a significant gain in the built-up area as it increased by 0.92% (35.2 hectares) from 1992 to 2004. Agriculture land area increased by 7% (296.8 hectares) and vegetation cover was reduced by 2.5% (104.7 hectares) during 1992 to 2004. In the period from 2004 to 2016, built-up land has drastically increased by 8.62% (363.9 hectares) and all other land covers reduced significantly. Overall, during 1992 to 2016, the built-up area increased by 9.4% (399.1 hectares), water bodies decreased by 0.5% (21 hectares), vegetation decreased by 4.9% (127.5 hectares), agriculture land increased by 4.2% (178 hectares), and barren land decreased by 5.2% or 428.9 hectares (Table 3 and Fig. 3).

The summarized results show that there is an increase in built-up land and agriculture land, while a drastic towns (Walker, 2011). In the absence of proper planning, such changes may result into depletion of



Fig. 4 Spatial distribution of LST for years 1992, 2004, and 2016.

decrease in barren land use, vegetation and water bodies. This shows that there is increased demand on land by the growing population due to increase in rural-urban migration, social, political and economic reasons, and particularly the Gilgit city which is the financial hub of the Gilgit-Baltistan province. The study validates earlier findings that due to political and economic reasons, there is rapid urban growth (Wali, 2016). A large portion of the barren land is utilized by the construction of government buildings that lead to further migration of population and generation of economic activity to surrounding areas of the city. One of the reasons for the decrease in water bodies that can be noticed from maps is due to encroachments and constructions of buildings within the banks of river and streams in Gilgit city.

Findings of the study are inconsistent with previous assessments of land-use changes in the Himalaya because of rapid urban growth (Anbalagan, 1993). Previously such changes in land use have also been observed in the form of expansion (encroaching surrounding agricultural lands, forests and rural environments) and intensity (increase in the density of the covered area, building, and population) within the forests, vegetated areas and water bodies (Izakovi^{*}cová et al., 2017), leading to increase vulnerabilities for environmental and climatic change effects (Tiwari et al., 2018).



Fig. 3 Spatial distribution of land use and land cover (LULC) change.

Computation of Land Surface Temperature

One of the key objectives of this research work was to generate a map representing absolute LST of the study area. LST values for the years 1992, 2004, and 2016 ranges between 15.1-48.4°C, 16-50.7 °C, 21.8-51.6 °C, respectively (Fig. 4). It was found that the highest LST

for the study area increased by 3.2 °C during 1992-2016 (Table 4). Similarly, the lowest LST for the area is also increased by 6.7 °C from 1992 to 2016 (Figure 4). These variations, in addition to the global climate changes, can be attributed to land-use changes with dominant built-up areas causing UHI effects. Rapid urbanization of the areas, e.g Markets or business areas of the Kashirote and Jutial localities can be noticed that there is a significant increase of LST. Overall, the maximum temperature can be noticed in the surrounding of the main city area, which are Jutial, Noor Colony, and Sakwar areas. These areas are mostly consisting of barren land and built-up areas (Fig. 4).

The results correspond with global temperature increase in the northern hemisphere, particularly with the unprecedented increase in Himalayas, which is estimated to be much greater than the global average of 0.74°C over the last 100 years (IPCC, 2007; Du et al., 2004). The findings could not be evaluated in detail in line with more localized context such as Fowler and Archer (2006) observing a 'conflicting signals of climate change in the western Himalayas on the basis decreasing mean and minimum of summer temperatures and increasing mean and maximum winter temperatures in Gilgit. However, it corresponds to some extent with Fowler and Archer (2006) in terms of highest LST increase of 3.2°C compared with lowest LST increase of 6.7 °C during 1992-2016.

In addition to global temperature trends, the temperature variations in Gilgit city seem to be greatly influenced by land-use changes. This is evident from temperature variation in city centers and peripheries, the former comprises of built-up areas dominated with vegetation and the later comprises of alluvial fans or slope lands, dominated by bare ground and rocks devoid of vegetation. LST in peripheral areas was higher than that of the built-up areas in city centers.

Table 4. Details of temperature change.

Year	Min	Average	Max	ST DIV
2016	21.803864	38.454342	51.654572	5.899267
2004	16.37445	36.599	50.786499	6.171077
1992	15.179504	36.084693	48.487305	6.012193

Co-relationship between NDVI, NDBI and NDWI with LST

The findings revealed higher temperatures in the surrounding areas of the city as compared to inside the city. Hence, in contrast to the previous studies (Buyadi, et al., 2013; Rogan, et al., 2013) which show higher temperatures inside city areas than the outside, the results of this study conclude Ibrahim, (2017) that sun's heat is absorbed into the barren land and rocks/mountains, making it warm earlier than other

land cover categories. On the other hand, other land cover categories (Ibrahim, 2017) that include vegetation areas have the capacity to retain heat for longer and release heat slowly at night (Ramírez et al 2012). In addition, one of the main arguments besides may be the urban area of Gilgit city has green fields, adjacent to the main market, big trees (around airport area and between buildings) streets and inner-city link roads are earthen/unmetalled roads that make it lowtemperature area. In addition, the variation in LST is also formed by the land type, as different types of land cover have potential in terms of heat absorption and radiation. In Gilgit city case, the built-up areas have higher absorption (as built-up areas have lower albedo) than barren land, whereas in surrounding city, is barren land that has lower absorption and releases heat early. Thus, results of this study are similar to those of Kant et al., (2009) whose outcome proved that bare land and built-up areas have a higher LST in the daytime as compared to other categories.



Fig. 5 Correlation between LST and NDWI for years 1992, 2004, and 2016.

To better understand the effects of LULC changes on LST there is a need to realize the relationship between land use types and thermal signatures (Weng, 2001). Based on randomly selected 50 points, NDVI, NDBI, and NDWI are computed from Landsat TM-5 1990,

2004, and Landsat OLI TIRS-8 2016. In a way to assess the relationship between NDVI, NDBI, NDWI and LST, a regression analysis was used to present the relationship quantitatively. Analysis based on linear regression showed the correlation coefficient (r) range from 0.90 to 0.92 in the year 1992, 2004, and 2016, respectively (Fig. 5-6). The observed relationship is a negative correlation between NDWI and LST, whereas, a positive correlation is found between NDBI and LST. From the analysis, it was observed that the vegetation covers had shown a considerable low radiant temperature throughout the year. The cultivated land and bare soil showed a significant increase in temperature. It is noted that the land-use changes have contributed to Urban heat island (UHI) intensity over the study area through the process of urban sprawl and degradation of vegetation area.



Fig. 6 Correlation between LST and NDBI for years 1992, 2004, and 2016.

Another important observation is that temperature around the urban centers can be attributed to vegetative cover, which is concentrated in built-up areas and lacked in peripheries. This contradicts the phenomenon of urbanization causing depletion of vegetative cover (Walker, 2011, Tiwari et al., 2018). Such a situation characterizes the pattern of the built environment, peculiar to northern Pakistan, comprising of fruit trees and a small kitchen garden, as an integral part of every house. In addition, the network of narrow roads and pavements also contain trees on both sides. In most of the cases, grapevines and other creeping plants also cover concrete and iron roofs. Such a mosaic of green areas within built-up environs increase resilience and adaptability of dwellers, on one hand by reducing the intensity of heat effect and on the other contributing to household food security obtained from vegetables and fruit production for household consumption. To overcome the heat stresses and other associated issues within the urban center, planners recommend increasing the extent of public green areas or green infrastructure (Dobrucká, 2009). Afforestation optimizes LST by altering local albedo and turbulent energy fluxes (Peng et al., 2014).

Conclusion

This research work monitored land use/cover changes over two and half-decade period using remote sensing and Google Earth's data and further, it studied how it influences the land surface temperature in Gilgit city. The approach was very reliable to achieve the objectives of this study, which revealed the variations in land use classes and their influence on LST. The maximum LST and minimum LST for the entire study area increased by 3.2 °C and 6.7 °C respectively over the period of 1992 to 2016. The results showed that there is a strong correlation between LST and LULC, as the LST values changed over the diverse classes. For example, barren land surrounding the city had higher temperature than vegetation areas inside the city. It was concluded that the water bodies (NDWI) and vegetative land (NDVI) are negatively correlated with the LST and built-up areas (NDBI) had positive correlation with LST. This work has investigated the relationship between LST and LULC change for a small portion of the HKH region. However, there is a need to expand the area of study in the future and explore the relationship of LST with regional climatic data to investigate the effects of LULC change on regional climate. This study will also help to understand the current ground realities and collect the valid local data (cities data) of the mountain regions like HKH, consequently making it easier to comprehend the climate change issues at the regional and national levels, which can be further shared with local communities to address the climate change adaptation and mitigation challenges.

The lower LSTs in the particular context of built-up areas in Gilgit shows the importance of vegetative cover in minimizing the heat island effect. In the context of urban centers in Asian highlands, it seems to be an effective adaptation measure. In addition to maintaining LST, fruit trees and kitchen gardens also enhance socio-economic resilience by contributing to the household economy and food security.

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