



RESEARCH ARTICLE

A cloud computing and spatial modelling-based assessment for land use and land cover dynamics and their association with urban surface temperature

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Abstract

Evaluation of spatial-temporal patterns is essential to ensure long-term sustainability in land use land cover (LULC) and associated operations, such as land surface temperature (LST). Our study employed and generated data on spatial-temporal changes in LULC and LST for 1990–2020 (the past three decades) in the Gujrat district of Pakistan using geoinformation modelling and Google Earth Engine (GEE). Our results indicated that "built-up area" increased by 6.1 % from 1990 to 2020. Agricultural land coverage decreased from 74.37 % in 1990 to 72.76 % in 2020; the "vegetation" showed a negative shift of 1.62 %, despite a decrease in "farm area" between 1990 and 2020. The mean normalised difference vegetation index (NDVI) value also reduced from 0.23 to 0.18 between 1990 and 2020. In the year 1990, the LST ranged from 10.2 to 44.2 °C, whereas in 2000, it ranged from 10.5 to 44.4 °C. The LST values ranged from 10.6 to 44.7 °C in 2010 and from 10.9 to 45.1 °C in 2020. The regression coefficients (R^2) between NDVI and LST were 0.82, 0.80, 0.79 and 0.75 in 1990, 2000, 2010 and 2020 respectively. The study's findings are significant for mitigating and adapting to climate change, given the link between LULC and LST. Thus, this enables the establishment of sustainable LULC planning and management protocol.

Keywords: climatic factors; geographical information system; land use land cover; modeling approaches; remote sensing

Introduction

Human existence heavily relies on land resources (1, 2). Considering the long-term alterations in land use land cover (LULC) resulting from human activities, which have substantial environmental impacts at the global, national and local levels, such as changes in surface energy and land surface temperature (LST), several challenges arise in the context of a growing population (3). Global environmental change has been recognized to be significantly influenced by changes in LULC. (4). Effective monitoring of LULC changes through earth observation data is essential for tracking ecological shifts and managing natural resources more efficiently (5).

There is a common conflation of the terms "land usage" and "land cover," which are technically distinct concepts (6). For instance, the term "land use (LU)" describes how a piece of property is put to work for various economic and social purposes (7). Nonetheless, land cover (LC) emphasizes the biological or physical state of terrestrial surfaces, such as forests and water bodies, among many others. There could be several factors behind the observed and expected transitions in LULC around the world (8). Such factors might include, but are not limited to, socioeconomic activities, meteorological and topographical conditions and the growing need for land to accommodate population influx (9, 10).

One of the most critical influences of LULC transitions is the change in the thermal characteristics of regions, which alters the climate in the long run. For billions of people living in rural and urban areas worldwide, climate is the single most important determinant of food supply, crop growth and economic stability (11). However, climate changes at various scales could potentially compromise the supply, creating economic and social challenges (12). For instance, anthropogenic activity-induced global climate change over the last several decades has significantly impacted vegetation and crop production. Given this situation, agrarian societies, such as Pakistan become vulnerable (13). Deterioration of LC reduces the land's profitability from LU in terms of area under measurable control (14, 15). To effectively respond to such deterioration, satellite images at various geographical, spectral and temporal resolutions have been successfully used as they provide a means to track and monitor LULC change, along with highlighting several drivers of these changes (16). However, their utilization has been restricted in arid and semi-arid environments for the development and assessment of LULC dynamics (17). Similarly, while the application of remote sensing data is growing to monitor and track LULC changes, there is still a gap when it comes to developing countries (18, 19). Even in developing countries, most of the focus of such research is on major urban regions. On the one hand, this focus on already urbanized regions shadows smaller metropolitan areas, which might experience comparatively rapid transitions in LULC (20). On the other hand, because LULC change poses an in-situ challenge that requires location-specific identification of its impacts, particularly on local thermal characteristics, it hinders informed planning and decision-making in smaller urbanising areas (21, 22).

Pakistan, the fifth most populous country in the world with a population of about 220 million, is one of the top 10 countries most at risk from climate change (23). To effectively plan for climate adaptation and sustainable urbanisation, it is essential to have a comprehensive understanding of how LULC changes over space and time and its relationship with LST (24). Such assessments can progressively serve as valuable benchmarks (25). Previous research has examined LULC changes and their relationship with climate indicators such as LST in specific regions of Pakistan. Many of these studies have focused on characterizing LULC changes and determining their impact on LST in urban areas to support climate adaptation efforts (26). However, the geographic scope of most of these studies is too narrow (e.g., studying only metropolitan areas). Similarly, the spatial-temporal assessment of LULC in some studies employed coarser-resolution datasets, which yielded less-than-optimal findings at the local to regional levels (27). It is also worth noting that, at present, Pakistan lacks a publicly accessible repository of historical data with a reasonably good resolution on long-term LULC trends and their impact on the local environment (28). This lack of data makes it harder to plan for sustainable natural resources, make decisions regarding the climate, design cities to be more climate resilient, keep tabs on ecosystems and address other pressing environmental issues (29). Considering this, there is a substantial need for a higher-resolution, large-scale study of LULC change and its possible relationship to climate indicators in Pakistan (30, 31).

Understanding the complex relationships between human activity, climate and environmental sustainability requires an investigation of changes in LULC and their relationship to fluctuations in LST (32). We can gain important insights into how

urbanisation, population expansion and socioeconomic variables affect environmental systems by looking at LULC dynamics and how they relate to LST. In this regard, the present research makes it easier to comprehend how local and regional climatic patterns are affected by anthropogenic changes in land resources, such as vegetation loss, urbanisation and agricultural intensification (33). By examining the temporal and spatial patterns of LULC change and its relationship to LST, the objectives of this study are to identify the drivers and underlying factors of LULC transitions, assess the impact of these changes on local thermal characteristics and provide valuable information for sustainable urban planning, climate adaptation and effective resource management (34, 35).

The findings of this analysis can have several potential implications, including informing policymakers and urban planners about the impacts of LULC change on climate, guiding land management strategies to promote sustainable development, enhancing climate resilience in urban areas and supporting evidence-based decision-making for addressing environmental challenges in highly populated and climate-vulnerable regions like Pakistan (36).

Furthermore, a thorough understanding of LULC-LST dynamics can significantly contribute to the formulation of effective mitigation and adaptation strategies to address the adverse effects of climate change and foster long-term ecological and socioeconomic sustainability. The main objective was to study the LULC and LST changes from 1990 to 2020 in the Gujrat district, Pakistan. By examining LULC dynamics and their relationship with LST, valuable insights can be gained into the impacts of urbanization, population growth and socioeconomic factors on environmental systems.

Materials and Methods

Study area

The Gujrat district is situated in northeastern Punjab at 32°34'23.7" N latitude and 74°4'57.6" E longitude, near the confluence of the Chenab River to the southeast and the Jhelum River to the northwest (Fig. 1). Jammu and Kashmir are located to its northeast. The Jhelum River separates it from the Jhelum district to the northwest and the Chenab River separates it from the Mandi Bahauddin district to the west and the Gujranwala and Sialkot districts to the east and southeast. Gujrat has a total size of roughly 3192 km² and a population of about 2.4 million. The district has a mild climate. Due to the proximity of the Azad Kashmir and Jammu mountain range, the summer months saw highs of 45 °C and occasional, intense heat waves. In the event of a severe winter, temperatures would fall below 2 °C. The average yearly rainfall was 778 mm. Most of the water used for residential and agricultural irrigation comes from aquifers deep below (37). The soil profile of the district revealed an alluvial complex of fine-to-medium clay, silt and sand (38).

Data gathering and preparation

Data collection, classification of LULC, assessment of changes, computation and evaluation of LULC and LST and determination of the connections between various LULC classes and LST are all important components of this study. The process is divided into two primary phases. In the initial phase, data were collected and LULCs were categorized using cloud computing via Google Earth Engine (GEE) across the entire research area (39). A wide variety of

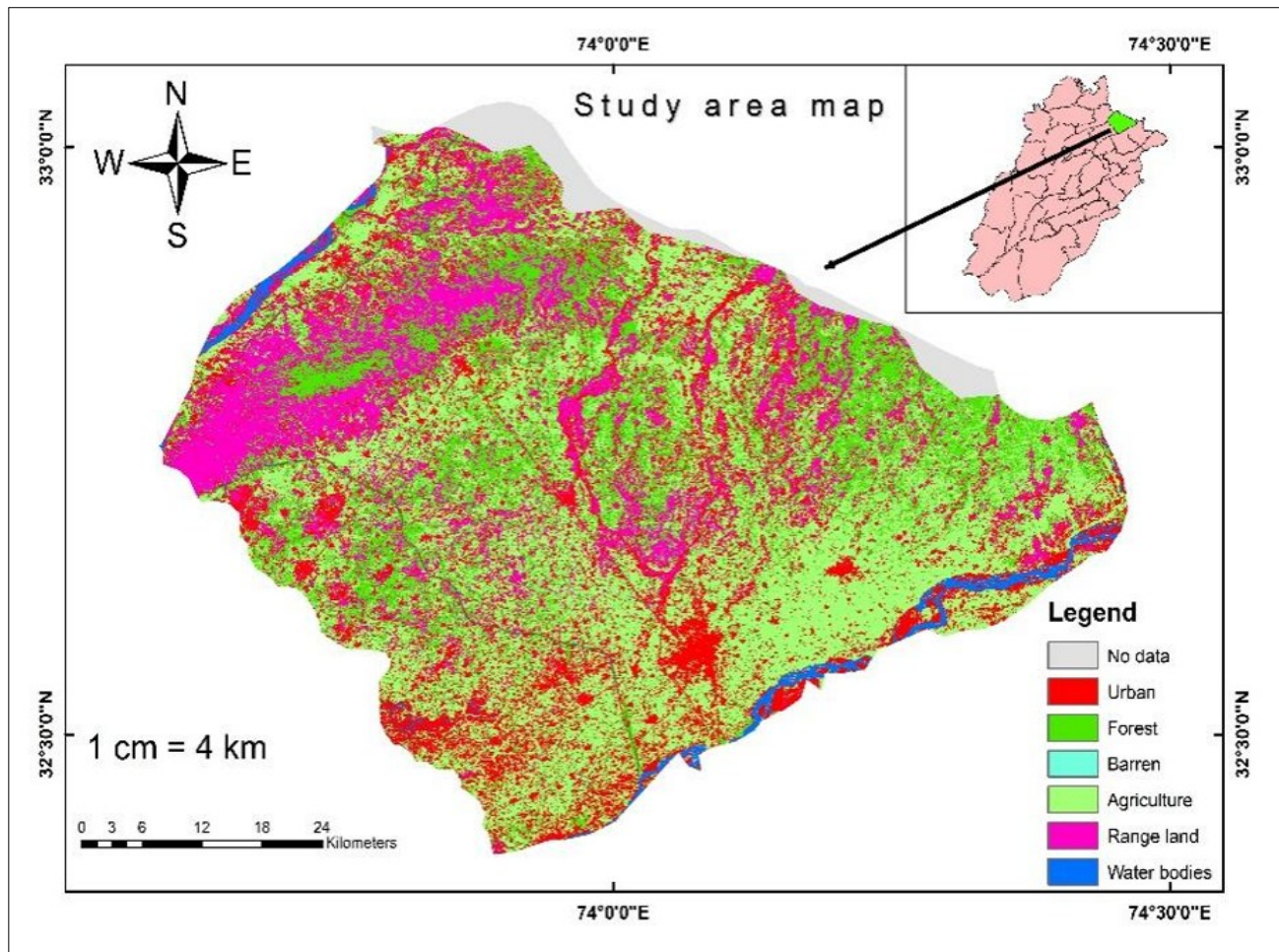


Fig. 1. Location map of the study area in the Gujarat district, Punjab, Pakistan (Software: ArcMap v. 10.2)

geo-information modelling tools were then used to investigate the possibility of improving LULC and LST and to evaluate any potential interactions between them (40). The study's approaches are schematically shown in Fig. 2. Prior to additional processing, Tier-1 surface reflectance (SR) data were obtained from the Landsat-8 operational land imager (OLI), the Landsat-5 thematic mapper (TM) and the thermal infrared sensor (TIRS). The Landsat-8 operational land imager (OLI), the Landsat-5 thematic mapper (TM) and the thermal infrared sensor (TIRS) provided Tier-1 SR data prior to additional processing. Given the gradual nature of LULC alterations, the study was conducted over four time periods (1990, 2000, 2010 and 2020). For 1990, 2000 and 2010, Tier-1 SR data from Landsat-5 TM were used; for 2020, data from Landsat-8 OLI were used. In addition to satellite-derived data, such as road networks, network data and vector data for provincial and district boundaries were also utilised. Table 1 provides information on the sources and dates of collection for all the data utilised in this study. Adjustments were made to get rid of atmospheric disturbances like haze by finding the darkest value for each pixel within every range and subtracting that amount from every pixel (41). The optimal pixel coverage and minimal cloud cover are attained by first removing the mean pixel values from the initial eight months each year (i.e., 1990, 2000, 2010 and 2020) but then clipping using a vector template of the Gujrat district.

Training and land use land cover classification

Land cover categorisation requires land cover data from many sources, such as VHR Google Earth pictures and the Copernicus Global Land Cover Layer (CGLS-100), as well as spatial indices like normalised difference vegetation index (NDVI) and LST produced from Landsat-5 and Landsat-8 tier-1 SR data. Usually, 500–1500 samples per class are collected as training points using a stratified sampling strategy (9). 70 % of this data is then used for training, with the remaining 30 % set aside for validation. In the training phase, the random forest (RF) classifier uses 70 % of the samples (about 3500 points per class) to perform supervised machine learning (ML)-based classification. To perform supervised ML-based classification, the RF classifier uses 70 % of the samples (about 3500 points per class) during the training phase. The remaining data (around 1500 samples) is set aside for validation purposes. The RF classifier is used to determine land use classifications every year; in this study, four specific years (1990, 2000, 2010 and 2020) were examined. To optimise results, the RF classifier was fine-tuned with an optimal tree value of 120. GEE was used as a pixel-based method to estimate the area for each land use category and the area estimate table and classified maps were exported locally. Change detection, which involves the analysis of multi-year changes in each class. The RF classifier was adjusted

Table 1. Information on the sources and dates of collection for all the satellite data

Sl. No.	Data type	Date of data collection	Scale	No. of bands	Path/Row
1	Landsat image	1990-04-05	30m TM	6	149/038
2	Landsat image	2000-03-25	30m TM	6	149/038
3	Landsat image	2010-03-28	30m TM	6	149/038
4	Landsat image	2020-03-12	30m ^{OLI}	10	149/038



Fig. 2. Process flow schematic explaining the overall working arrangement in this study.

with an ideal n tree value of 120 to maximize outcomes. Each land use category's area was estimated using a pixel-based approach using GEE and the area estimate table and classed maps were exported locally. Quantum geographic information system (QGIS), an open-source program, was used for change identification, which involved analysing multi-year changes in each class (42).

Assessment of land surface temperature and normalized difference vegetation index alteration

Change detection involves examining changes in the state of an object over time. In land use research, change detection is an invaluable tool for visualising spatial patterns across diverse land use classifications. While pre- and post-classification methods have been used for change analysis, post-classification change detection has become the industry standard. It is used in most case studies (43). Post-classification change detection involves comparing classified maps from different periods at the pixel level, reducing the impact of sensor and environmental factors and enabling a more detailed analysis of how various land use types change over time. This methodology evaluates the rates and magnitudes of change for each classification independently, yielding precise results as demonstrated by prior research (44).

In this study, post-classification comparison was employed to evaluate temporal shifts in LULC for the years 1990, 2000, 2010 and 2020. The generation of LULC-classified maps for each year and their subsequent analysis were facilitated using QGIS's Semi-Automatic Classifier Plugin, Python programs (Pandas, Matplotlib, Seaborn) and Microsoft Excel. The resulting alteration maps and matrices provide a means to visualise the percentage shifts, shift magnitudes and transitions across classifications.

The mean value for each year was determined by filtering the top of atmosphere (TOA) Tier-1 data from Landsat 5 and 8 for the summer (May through August). Subsequently, a shape file was used

to crop the photos to define the study's scope. The LST was calculated from TOA data obtained from Landsat 5 (1990, 2000 and 2010) and Landsat 8 (2020). Unlike Landsat-8 OLI/TIRS, which contains two thermal bands, Landsat-5 TM has only one thermal band (band 6). Bands 6 of the TM and 10 of the TIRS were used to estimate the LST. Band 11 of TIRS was avoided because of errors in calibration, according to a report from the US Geological Survey (44).

Converting digital numbers to spectral radiance

Digital numbers (DN) from the thermal bands can be converted into spectral radiance ($L\lambda$) using Equations (1) and (2). The following formula provides the resulting upper atmospheric radiance (L) in $(m^2 \times ster \times \mu m)$.

$$(L\lambda) = \frac{LMAX - LMIN}{QCALMAX - QCALMIN} \times (QCAL - QCALMIN) + LMIN \quad (Eqn.1)$$

Where LMAX = maximal spectral radiances (15.600 for TM), QCAL = band 6 Digital Number values, minimal spectral radiances, or LMIN (1.238 for TM) and the highest DN value (255) is QCALMAX.

Metadata files accompanying Landsat pictures are mined for their value of LMAX, LMIN, QCAL_{MAX} and QCAL_{MIN}. For the Landsat 8 OLI thermal band, the best distinctive radiance ($L\lambda$) is considered, disbursing the subsequent equation (2) provided by (32);

$$(L\lambda) = ML \times QCAL + AL \quad (Eqn.2)$$

Where,

ML = multiplicative rescaling factor for specific band (0.0003342)

QCAL = digital numbers of band 10

AL = additive rescaling factor for specific band (0.1).

Converting spectral radiance ($L\lambda$) to at-satellite brightness temperature T

$$TB = \frac{K2}{\ln\left(\frac{K1}{L} + 1\right)} \quad (\text{Eqn.3})$$

Using the following equation (3), we got the TOA emissivity from the spectral radiance. Equation 3, where TB is the brightness temperature measured by the satellite in Kelvin (K), L is the spectral radiance and K1 and K2 are sensor-specific calibration constants. The K1 and K2 values for Landsat-5 TM are 607.76 and 1260.56. In contrast, K1 for Landsat-8 OLI is calculated at 774.89 and K2 at 1321.08.

$$LST = \frac{TB}{1 + \left(\frac{\lambda \times TB}{p}\right) \times \ln \epsilon} - 273.15 \quad (\text{Eqn.4})$$

LST stands for land surface temperature (°C), TB for at-satellite brightness temperature (K), λ for wavelength of emitted light (11.5 μm), p for 1.438×10^{-2} m and ϵ for emissivity (ranging from 0.97 to 0.99). $\lambda = 1.438 \times 10^{-2}$ m ϵ = emissivity (ranging from 0.97 to 0.99) λ = wavelength of emitted radiation (11.5 μm).

Equation (5) can be used to compute emissivity:

$$\epsilon = 0.0004 P_v + 0.986 \quad (\text{Eqn.5})$$

Where,

P_v = proportion of vegetation.

Equation (6) can be used to determine the percentage of vegetation, P_v .

$$P_v = \left(\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \right) 2 \quad (\text{Eqn.6})$$

The normalized difference index (NDVI), lowest normalized difference vegetation index (NDVI min) and greatest normalized difference vegetation index (NDVI max) were the pixel-specific variables used in this investigation. The Vegetation Proportion (P_v) and emissivity (ϵ) values were calculated using the same formula. The following formula was used to determine NDVI: (45):

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (\text{Eqn.7})$$

Where,

NIR stands for a near-infrared band (TM and ETM+ band 4, OLI band 5)

RED stands for the red band (TM and ETM+ band 3, OLI band 4)

Evaluating spatial consistencies among land use land cover change and land surface temperature

Previous studies have used regression techniques to establish relationships between LST and LULC types. However, given the spatially dynamic nature of LST and LULC, it is preferable to use a regression method that accounts for these differences. In this study,

geographically weighted regression (GWR) was employed to investigate the potential relationship between LULC types and LST. Ordinary least squares regression is another option for exploring the relationship, but it is less favourable because it is global in nature and inadequate for understanding local spatial interactions between the dependent and explanatory variables. In contrast, GWR is a more appropriate approach that allows for the examination of local spatial relationships (46).

Results

Land use land cover change and transitions

We analysed the LULC classification of the Gujrat district from 1990 to 2020 and examined various land characteristics. The study found that in 1990, only 3 % of the total area was classified as "built-up," which increased to 4.89 % in 2000 and is projected to reach 9.12 % by 2020 (Table 2). The growth in the "built-up area" resulted in a 6.1 % increase in impervious surface in the study area. Agricultural land coverage in the Gujrat district decreased from 74.37 % in 1990 to 72.76 % in 2020, while "vegetation" showed a negative shift of 1.62 %, despite a decrease in "farm area" from 1990 to 2020. In 1990, "other" types of water accounted for 3.27 % in the Gujrat district, which has since dropped to 2.44 % by 2020 (Fig. 3). Range land was noted at 16.14 % in 1990, but it decreased to 13.08 % in 2020 in the study area. Over the past three decades, we have observed a shift from forested and unpaved regions to areas occupied by buildings and roads, due to rapid urbanisation in Pakistan. Bare soil made up 2.5 % of the landscape in 1990, which had fallen to 0.74 % in 2020. The amount of "bare soil" has declined in recent years. Gujrat district is rapidly expanding in terms of its flora and human population, attracting people from surrounding areas and smaller nearby cities.

Evaluating vegetation dynamics through normalized difference vegetation index

The spectral properties of vegetation are crucial for vegetation metrics that are derived from satellite imagery. The NDVI is a commonly used metric that measures the amount of vegetation in each area because plants absorb visible light for photosynthesis and reflect most near-infrared (NIR) radiation. In this study, NDVI values were estimated from Landsat bands and vegetation cover in the study area was mapped using ERDAS Imagine 2015 and ArcGIS 10.1 software. The results of this analysis showed that the maximum NDVI decreased from 0.62 in 1990 to 0.45 in 2020, whereas the minimum NDVI decreased from -0.17 to -0.10 over the same period. In addition, the mean NDVI value dropped from 0.23 – 0.18 in the study area (Fig. 4). These findings suggest that the average NDVI has been over time, indicating a decrease in vegetation cover.

Table 2: Land use land cover (LULC) area coverage and change from 1990 – 2020 in the Gujrat district

LULC classes	1990		2000		2010		2020		Change 1990 to 2020	
	Ha	%	Ha	%	Ha	%	Ha	%		
Urban	9640	3.02	15606	4.89	20440	6.40	29113	9.12	19473	6.10
Forest	2730	0.85	2720	0.85	2300	0.72	2180	0.68	-550	-0.17
Barren	7990	2.50	5842	1.83	2690	0.84	2365	0.74	-5625	-1.76
Agriculture	237400	74.37	234560	73.48	232630	72.88	232240	72.75	-5160	-1.61
Range land	47220	14.79	47480	14.87	48520	15.20	41722	13.07	-5498	-1.72
Water	10440	3.27	9212	2.88	8840	2.77	7800	2.44	-2640	-0.82
Total	319200	100	319200	100	319200	100	319200	100	-	-

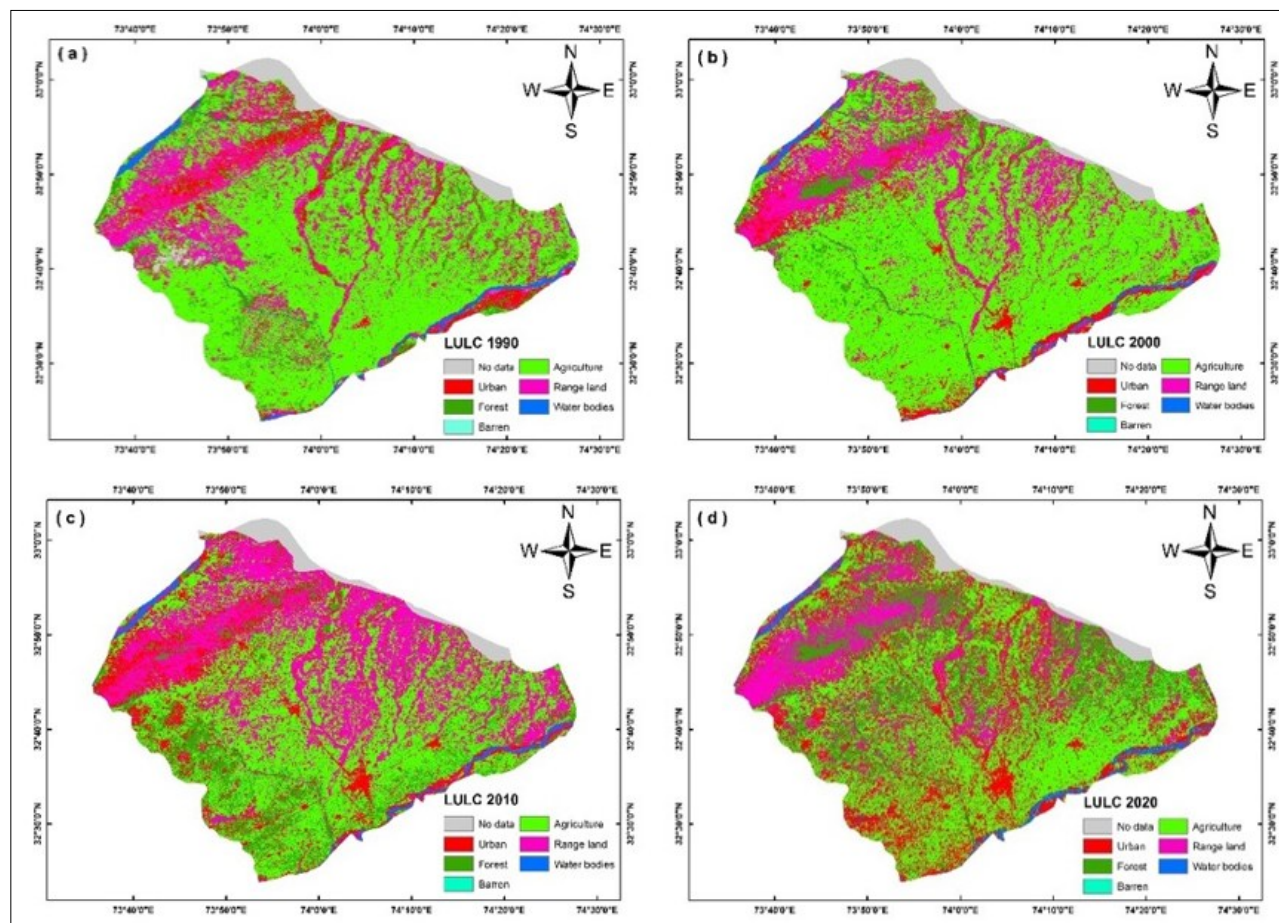


Fig. 3. Land use land cover (LULC) classification of the study area during the past three decades (1990–2020) (Software: ArcMap v. 10.2).

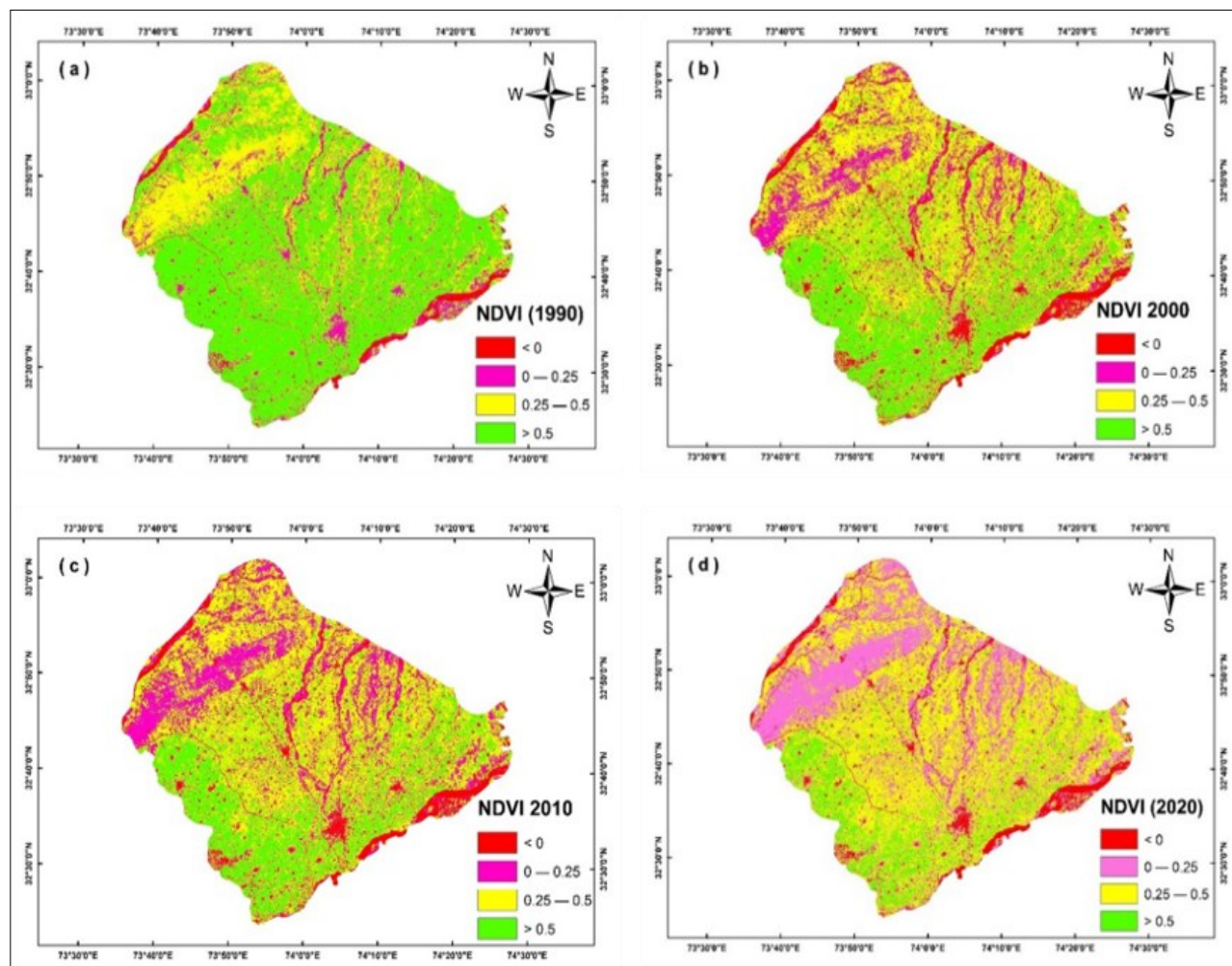


Fig. 4. NDVI distribution in the area over the past three decades (Software: ArcMap v. 10.2).

The highest NDVI value of 0.62 in 1990 suggests a high concentration of plant life, whereas the lowest NDVI value of -0.17 indicates the presence of water bodies in the study area. The maximum NDVI value in 2000 was 0.57, indicating full vegetation cover, whereas the minimum NDVI value was -0.14, indicating the presence of water bodies and barren soil (Table 3). The maximum NDVI value in 2020 remained the same as that in the previous year at 0.45, indicating an adequate quantity of vegetation cover, whereas the minimum NDVI value decreased to -0.10, indicating bare soil due to reduced vegetation cover and lower rainfall. Overall, the NDVI values in the study region declined by 0.05 pp between 1990 and 2020.

Spatial-temporal disparities in land surface temperature

This study revealed that the LST increased from 1990 to 2020 owing to a subsequent increase in built-up areas, which generated a significant thermal signal (Fig. 5). The LST ranged from 10.2 to 44.2 °C and 10.5 to 44.4 °C in 1990 and 2000, respectively. In, it was 10.6–44.7 °C and 10.9–45.1 °C, respectively (Table 3). In the urban areas of the Gujarat region, built-up areas experienced higher temperatures owing to the developed infrastructure. Our study highlighted that the average LST values increased from 27.2 to 28 °C between 1990 and 2020, as mentioned earlier. The comparison of Fig. 4 and 5 indicates that the southern part of the Gujrat region experienced a decrease in NDVI and an increase in LST due to infrastructure development and the conversion of cropland and vegetation into urban areas.

Statistical relationships

The relationship between temperature and vegetation cover (NDVI) in the study area was investigated and the regression analysis indicated a negative correlation between temperature and NDVI. In the present study, goodness-of-fit coefficients (R^2) of 0.82, 0.80, 0.79 and 0.75 were observed for 1990, 2000, 2010 and 2020, respectively (Fig. 6). Regression analysis showed that the temperature increase was directly proportional to NDVI. This may be attributed to reduced vegetation and other land features.

Discussion

The impact of LULC changes resulting from industrialisation has been widely recognised as a significant driver of various issues, particularly in developing countries. Urbanisation, for instance, has been associated with ecological degradation, loss of biodiversity and vegetation and increased impermeable surfaces. These changes in LULC have not only local but also national and global impacts, leading people to feel uneasy in urban settings. Moreover, urbanisation has increased the vulnerability of areas to natural disasters like floods and storm surges.

Previous studies stated that the urban heat island (UHI) effect and the local energy balance are intensified by the conversion of natural land cover to impervious surfaces. The observed decrease in vegetation cover and increase in the thermal hotspots are also in line with studies carried out in Pakistan. Assessments on LULC shifts are essential for various purposes, including climate mitigation, erosion control and sustainable land use planning (47). With

increased human influence and the need for arable land, there have been significant changes in the distribution of bare soil, water bodies and cultivated areas. Hence, where these LULC changes have been experienced and how they contribute to changes in the thermal characteristics of urban areas provide useful insights for appropriate measures. In this regard, our research can assist policymakers in developing strategies to better manage land resources by providing a key monitoring base for current studies on land management, along with highlighting several regions requiring immediate attention from relevant authorities to take measures to reduce the UHI effect.

The amplified impermeable surface of cities is responsible for the consequences of the UHI effect, characterised by a pronounced geographic pattern in LST. To develop effective measures to adapt to UHI, it is crucial to have information about LST distribution at the municipal and state levels (48).

Due to rapid population growth, cities in developing countries often lack the capacity to tackle the challenges of urbanisation. Consequently, the increasing urban temperature (as presented in this study) could have detrimental effects on the health and lives of millions of urban residents. It is therefore imperative to evaluate the spatial-temporal trends and patterns of urban warming to identify potential adaptation solutions. However, for developing countries such as Bangladesh and Pakistan, there is presently insufficient information available (16). Mid-level highly urbanised cities experienced a greater increase in urban surface temperature due to rapid and often unplanned urban expansion, limited green infrastructure and insufficient implementation of climate-responsive urban planning policies. Hence, due attention should also be given to mediocre urban regions (i.e., Gujrat) and appropriate mitigation measures should be implemented without overlooking them in favor of already urbanised areas (1, 49). The same conclusion was reported by previous researchers who showed that land surface temperature (LST) rises significantly with the development of the urban area in fast-growing cities (46).

Considering the increasing LST resulting from LULC changes in Gujrat, it is advisable to promote strategies such as the implementation of light-colored roofs, the planting of shade trees with high canopies and the development of both horizontal and vertical green spaces within buildings. These measures have been demonstrated to effectively mitigate the adverse effects of urban heat islands (UHI) and enhance the urban microclimate (16). However, before implementing these strategies, it is essential to conduct comprehensive land-use planning to prevent unplanned urban expansion and mitigate the future impacts of heat islands. This research will provide policymakers with valuable insights to take proactive measures.

Policymakers should include geospatial monitoring systems and cloud computing platforms like Google Earth Engine in urban planning processes to provide real-time monitoring of LULC changes and thermal hotspots. Local governments need to set up urban growth boundaries (UGBs) to limit unplanned urban expansion and preserve peri-urban agricultural land and ecological zones. The

Table 3. NDVI and LST summary statistics for different

Years	NDVI			LST		
	Min	Max	Average	Min	Max	Average
1990	-0.17	0.62	0.23	10.2	44.2	27.2
2000	-0.14	0.57	0.22	10.5	44.4	27.45
2010	-0.11	0.52	0.21	10.6	44.7	27.65
2020	-0.1	0.45	0.18	10.9	45.1	28

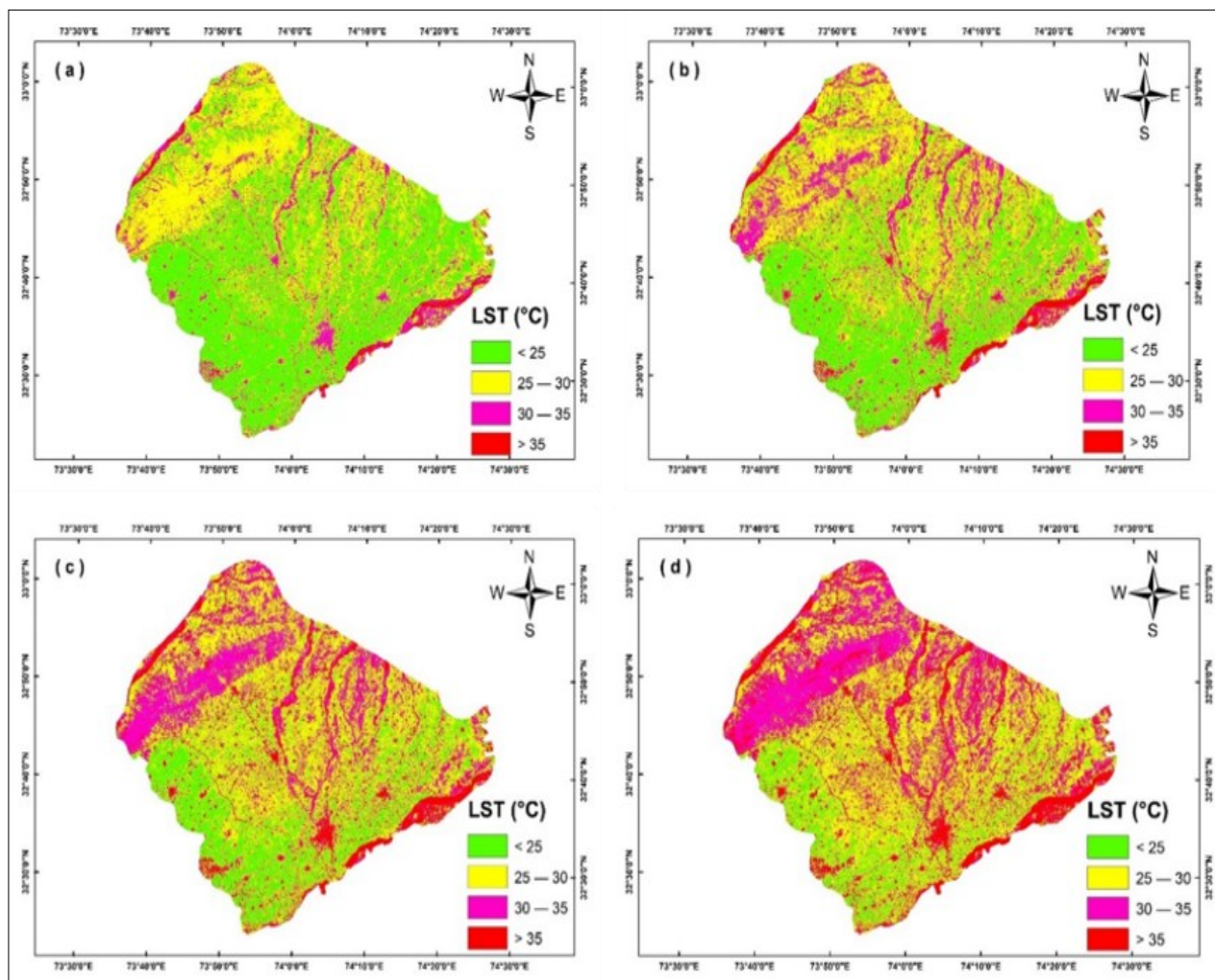


Fig. 5. Land surface temperature distribution in the study area during 1990–2020 (Software: ArcMap v. 10.2).

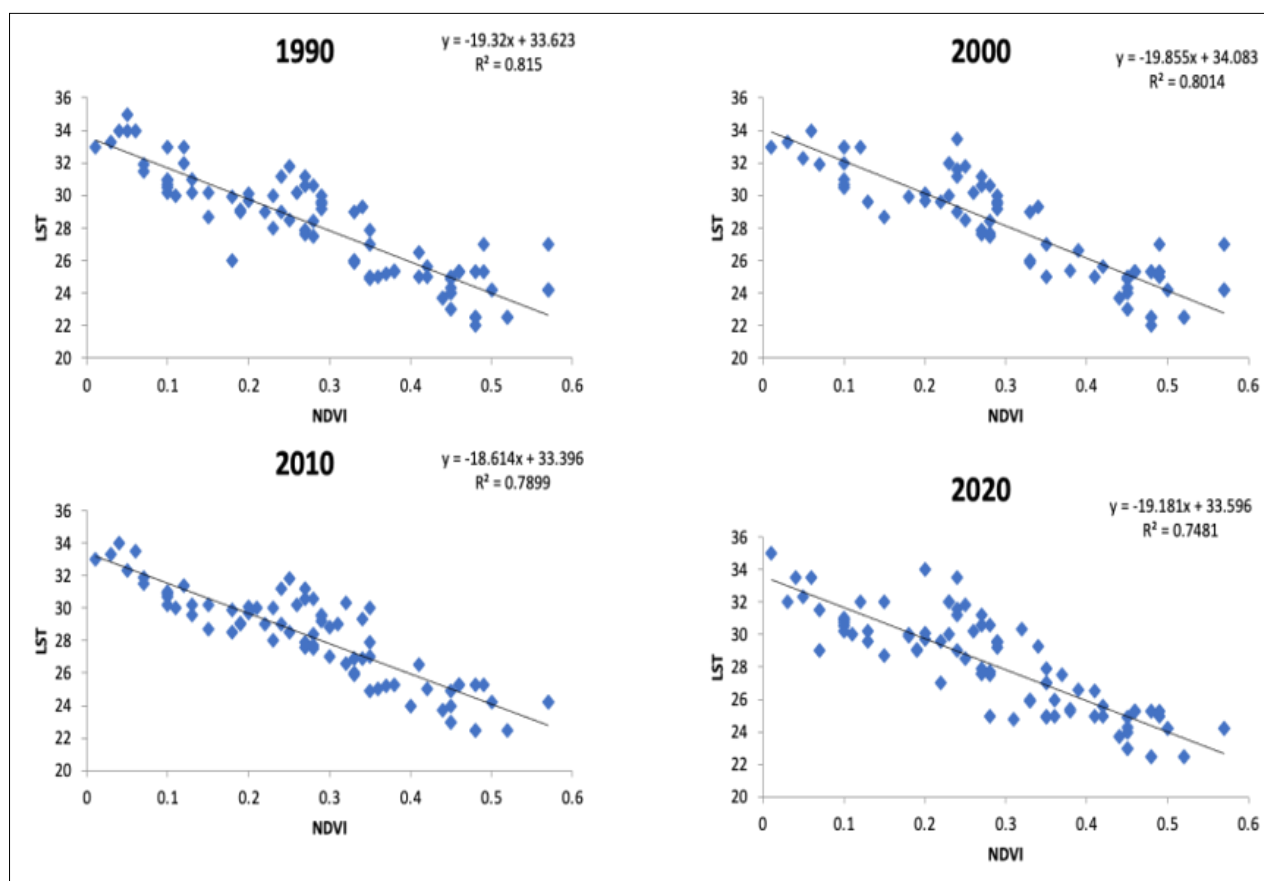


Fig. 6. Observed relationship between normalized difference vegetation index (NDVI) and land surface temperature (LST) during different periods across the past three decades.

implementation of urban greening should be based on the principle of mandatory green belts, roadside plantation programs, vertical gardens and minimum green space standards for new housing schemes and commercial developments. Enhancing urban tree canopy covers can play a significant role in lowering the local surface temperature and make urban areas more resilient to climate change. The study also underscores the importance of inter-agency coordination between the urban planners, environmental protection agencies and disaster management authorities in order to create integrated urban climate adaptation plans. Thermal monitoring systems based on remote sensing should be integrated into smart city projects, to aid in evidence-based decision making and in long-term sustainability planning.

Conclusion

Using satellite imagery, this research examines changes in land use land cover (LULC) and land surface temperature (LST) in Gujrat, Pakistan, over the past three decades (1990–2020). To accomplish this, cloud-based technology, namely Google Earth Engine (GEE) and geographic information models are integrated. Spatial heterogeneities are investigated and the potential relationship between LULC types and LST is evaluated. The growth in "built-up area" resulted in a 6.1 % increase in impervious surface in the study area. Agricultural land coverage in the Gujarat district decreased from 74.37% in 1990 to 72.76 % in 2020, while "vegetation" showed a negative shift of 1.62 %, despite a decrease in "farm area" between 1990 and 2020. The mean normalised difference vegetation index (NDVI) value also reduced from 0.23 to 0.18 (1990–2020). The LST ranged from 10.2 to 44.2 °C, 10.5 to 44.4 °C, 10.6 to 44.7 °C and 10.9 to 45.1 °C in 1990, 2000, 2010 and 2020, respectively.

Additionally, evaluating LST and its correlation with LULC changes will inform adaptation-related decisions and policies in Pakistan. Despite the research's comprehensive nature, the authors acknowledge significant limitations. For instance, the analysis does not consider other factors (such as airflow and building structures) that may be sensitive to local LST fluctuations. Therefore, future work can incorporate such data if possible. This could result in a more comprehensive set of information. Our work and findings provide a baseline for the study area and enable more detailed analyses at the local level. Furthermore, future research could assess the impact of LULC changes on various other phenomena, such as vulnerability to natural disasters, land degradation (e.g., soil erosion), resource conservation and alterations in ecosystem services. The LULC data generated in this study could be useful in this regard. This research not only contributes to understanding local climate dynamics in Gujrat but also offers valuable insights for informed urban planning and sustainable land management practices in similar contexts.

The integration of higher resolution remote sensing (RS) data with real-time cloud computing platforms should be a focus of future research to enhance the accuracy of LULC and urban surface temperature monitoring. Further research is needed to consider socio-economic and climatic factors to account for the complex factors driving urban thermal dynamics in various city typologies. It is also recommended to conduct a comparative multi-city analysis across South Asia to prepare specific urban heat mitigation and sustainable planning strategies for the region.

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Authors' contributions

SST, MF, RA, DA, MM¹ and MM² contributed to conceptualisation and methodology. MS, SH, NPA, RG, MF, RA, DA, MM¹ and MM² contributed to software, validation, formal analysis and data curation. SST, SH, NPA, SAQ, RG, MF, RA, DA, MM¹, MM² and BNR contributed to investigation. NPA, SAQ, RG, MF, RA, DA, MM¹, MM² and BNR contributed to resources. SST, MS, SH, NPA, SAQ, RG, MF, RA, DA, MM¹, MM² and BNR contributed to writing, review and editing of the manuscript. MS, SH, MM¹ and MM² supervised the study. MM¹, MM² and BNR contributed to visualisation, project administration and funding acquisition. All authors have read and approved the final manuscript [MM¹- Muhammad Majeed and MM² - Murad Muhammad].

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

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