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Climate change-induced spatiotemporal variations of land use land cover by using multitemporal satellite imagery analysis

Izhar Ahmad[a,*], Muhammad Waseem[b], Sadaquat Hussain[c] and Megersa Kebede Leta[d]

[a] Department of Civil Engineering, Ghulam Ishaq Khan Institute of Engineering Sciences and Technology, Topi 23640, Pakistan
[b] School of Interdisciplinary Engineering & Sciences (SINES), National University of Sciences & Technology (NUST), Sector H-12, Islamabad 44000, Pakistan
[c] Aror University of Art, Architecture, Design and Heritage, Sukkur 65170, Pakistan
[d] Faculty of Civil and Environmental Engineering, Jimma Institute of Technology, Jimma University, Jimma 378, Ethiopia
*Corresponding author. E-mail: gcv2339@giki.edu.pk

ABSTRACT

This study examines Islamabad's landscape changes over four decades, attributing land degradation to shifts in land use and cover. Using Landsat imagery from 1980 to 2023, it analyzes urban growth in five categories. By employing the normalized difference vegetation index (NDVI) and normalized difference built-up index (NDBI), it notes built-up areas expanding to 61% by 2023, agricultural land contraction, and fluctuating forest cover. Water bodies and bare land decrease significantly. With high accuracy values, NDVI fluctuates from +0.4523 in 1980 to +0.1596 in 2010, rebounding to +0.4422. Fluctuations in barren soil, vegetation, and built-up areas potentially contribute to temperature and rainfall changes. The study explores LULC and land surface temperature correlation. Surveyed respondents (755) express concerns about environmental changes, anticipating reduced rainfall and increased drought. Valuable for sustainable development goals, the study informs policy formulation for effective urban planning and land use control.

Key words: climate change implications, land use land cover change, Landsat imagery, remote sensing, sustainable development goals

HIGHLIGHTS

- This study unveils Islamabad's four-decade urban expansion and its transformative impact on land use.
- This study explores how this growth has led to significant environmental changes, affecting land surface temperature and water resources.
- This study highlights the city's growing climate awareness, emphasizing the need for sustainable urban planning.

1. INTRODUCTION

Alterations in land use and land cover (LULC) exert a profound impact on the environment, spanning across local, regional, and global scales (Conacher 2009). These LULC changes can stem from both human-induced and natural factors (van Lynden & Oldeman 1997). The trajectory of urban expansion, in particular, is significantly influenced by factors such as population growth, urban sprawl dynamics, shifts in local and regional environmental attributes, the diminishing availability of agricultural land, and the consumption of various other environmental resources (Kertész 2009; Post *et al.* 2009; Elmqvist *et al.* 2013). In countries like Pakistan, individuals migrate from rural to urban areas in pursuit of improved amenities, thereby exerting pressure on the available natural resources. Urbanization, driven by economic development, emerges as an indispensable phenomenon, leading to the growth of urban populations and a substantial demand for housing (Jan *et al.* 2008; Kugelman 2013; IOM 2019; Abdul & Yu 2020). The significant population growth gives rise to a myriad of environmental and societal challenges, encompassing concerns such as climate change, impoverished livelihoods, interruptions in economic progress, and the constraints of depleting and deteriorating water resources (Patra *et al.* 2018; Murmu *et al.* 2019). Of growing concern, projections indicate that as much as 70% of the global population could be residing in urban areas by the year 2050 (Zhang 2016; Malik *et al.* 2017). Urbanization and population growth drive the spatial and physical expansion of cities, leading to an expansion of built-up areas, an abundance of impermeable surfaces, and significant alterations in climatic and hydrological conditions within urban environments (Wu *et al.* 2011; Sakieh *et al.* 2015). Unplanned urbanization gives rise to a host of significant challenges, encompassing issues such as inadequate housing conditions, traffic congestion, the provision of essential services to the populace, public health concerns, unemployment, educational disparities (Aziz *et al.*

2015), the emergence of slums, increased crime rates, limited access to clean water and electricity, and environmental degradation (Tanguay *et al.* 2010). All of these factors collectively exert a substantial influence on the quality of urban life (Ghalib *et al.* 2017). The principal driver of urban sprawl in emerging nations is the proliferation of unplanned housing developments, often occurring at the expense of converting agricultural areas into urban centers (Khalifa 2015; Li *et al.* 2017). Socioeconomic and biophysical factors play a pivotal role in influencing the extent and magnitude of LULC changes across diverse regions of the world (Gutman & Radeloff 2016). The primary drivers of changes in LULC are uncontrolled population growth, the swift pace of urbanization, and regional-scale shifts in agricultural expansion or contraction (Lambin *et al.* 2003; Hassan *et al.* 2016). Alterations in LULC are intricately linked to human activities, either through direct or indirect influence (Manandhar *et al.* 2009), and can exert an impact on climate dynamics. In the study presented by Samie *et al.* (2017), it is anticipated that in the foreseeable future, there will be an increase in built-up and agricultural land, accompanied by a reduction in forested areas and water bodies. The expansion of cities in Pakistan has occurred haphazardly, encompassing both an increase in urban size and quantity, as noted in the studies by Kombe (2005) and Busgeeth *et al.* (2008). While there are no universally established criteria for classifying cities as planned or unplanned, certain guiding principles are often employed, including considerations of population density, deliberate growth patterns, and the availability of green spaces (Mamun *et al.* 2022; Mallik *et al.* 2023).

Given the enduring consequences of LULC changes, particularly in urban areas characterized by micro-climate heating, it is imperative to engage in comprehensive studies to investigate their long-term impact on land ecology (Butt *et al.* 2015). Considering that LULC stands as a pivotal component within such investigations, it is essential to recognize the multitude of activities capable of altering it. Several studies have compiled comprehensive summaries detailing the impacts on LULC in diverse regions across the globe, considering factors such as agricultural expansion (Hietala-Koivu *et al.* 2004), urban sprawl (Bhat *et al.* 2017), and large-scale engineering initiatives encompassing accessibility and energy projects (Velastegui-Montoya *et al.* 2020; Llerena-Montoya *et al.* 2021). The evaluation of green vegetation is determined by applying normalized difference vegetation index (NDVI) thresholds. The NDVI standards span a range from 1.0 to −1.0 (Farooq & Qurat-ul-ain 2012). Negative NDVI values are indicative of water bodies and urban areas, while pixels exhibiting varying degrees of vegetation coverage, from extremely low to high, are characterized by positive NDVI values (Ahmad 2012). NDVI standards approaching 0 are indicative of bare soil or bare dirt (Lambin *et al.* 2003). It is frequently employed in remote sensing (RS) research due to its ability to provide pertinent evidence for the inclusion and study of vegetation (Ahmad 2012; Harris *et al.* 2014). RS and geographic information systems (GIS) are indispensable techniques (Uddin *et al.* 2013) employed for the assessment of urban dimensions, population density analysis, LULC mapping, and the evaluation of ecological impacts associated with urban development over specific temporal intervals (Majeed *et al.* 2021b). RS provides cost-effective and timely access to accurate LULC as well as vegetation cover data, precisely when needed (Fan *et al.* 2007). GIS efficiently manage and decipher geographical data, representing a critical and foundational necessity within this realm of research (Fan *et al.* 2007). RS data serve as a valuable tool for the mapping of LULC (Ayele *et al.* 2018). Landsat 5 Multispectral Scanner (MSS) (Vogelmann *et al.* 2001), Landsat 4–5 Thematic Mapper (TM) (Egorov *et al.* 2019), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) (Choate *et al.* 2021), and Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) (Ji *et al.* 2015) temporal sensor data are instrumental in the field of LULC mapping (Omran 2012). It aids in identifying the fluctuations linked to LULC attributes by conducting statistical and graphical assessments of both historical and contemporary satellite datasets, offering valuable insights into the evolving conditions (Arora & Wolter 2018). This study deciphers the applications of specific categorization methods, employing field data to provide a comprehensive explanation (Pal & Ziaul 2017). Researchers from diverse regions across the globe, spanning from northwest Ethiopia (Tewabe & Fentahun 2020), West Africa (Nyamekye *et al.* 2018), Ethiopia (Udin & Zahuri 2017), Malaysia (Udin & Zahuri 2017), Zimbabwe (Maviza & Ahmed 2020), Bangladesh (Rahman *et al.* 2017), Southern Africa (Harris *et al.* 2014), Iran (Tariq & Shu 2020), Nepal, China (Fan *et al.* 2007), northern Ethiopia (Ayele *et al.* 2018), Brazil (Lu *et al.* 2013), Iraq (Rahman *et al.* 2021), to Turkey (Nowacki & Abrams 2015), have undertaken extensive investigations into various methodologies aimed at assessing and managing LULC changes and degradation through the utilization of RS data. Climate change is widely recognized for its direct influence on agriculture in Pakistan, consequently affecting the livelihoods of lowland farmers. The evaluation and control of LULC transformations through RS data have been the subject of various investigations across several regions in Pakistan, including southern Punjab (Hussain 2018), Faisalabad and Multan (Ahmad 2012), Vehari (Farooq & Qurat-ul-ain 2012), Sindh (Uddin *et al.* 2013), Azad Jammu and Kashmir (Majeed *et al.* 2021a), Multan (Ibrahim 2017), Lodhran (Akar & Güngör 2015), and Peshawar, Khyber Pakhtunkhwa

(Raziq *et al.* 2016). These studies collectively contribute to a more comprehensive understanding of the intricate interplay between climate change, LULC, and agriculture in the region.

Over the past two to three decades, Islamabad, the capital city of Pakistan, has experienced urban sprawl driven by various factors, including migration, the development of new infrastructure and housing initiatives, and internal population displacement resulting from terrorism. Between 1972 and 2009, the city's geographical footprint expanded by 87.31 km^2, primarily due to the reduction of forest cover and the transformation of natural habitats. This urban growth and its associated drivers have significantly shaped the city's landscape during this period (Butt *et al.* 2012). During the same timeframe, the urban areas expanded from 58.854 km^2 in 1990 to 309.697 km^2 in 2018, exhibiting a remarkable growth of 426.21%. Over the period spanning from 1990 to 2018, Islamabad's urban region surged from 6.22% to 32.74% of the entire land area, signifying a substantial shift in its land use pattern (Rauf & Weber 2021). The expansion of Islamabad's urban area can be attributed to several contributing factors, including a growing population, enhanced transportation infrastructure, updated urban planning, and recent developments in the industrial and real estate sectors. From 1979 to 2009, the city's population increased by half, surging from 0.559 million to 1.095 million. A more substantial population growth occurred between 2009 and 2019, with the city's population increasing from 0.777 million to 1.095 million. This period witnessed significant advancements in commercial, industrial, residential, and transportation infrastructure, as well as an uptick in administrative services, all contributing to the overall population increase (Kamran *et al.* 2023).

This research employs GIS and RS techniques to assess the spatial and temporal transformations in Islamabad's land use. The primary objective is to investigate the current state of different land use types and track any alterations that have occurred over the past four decades. These spatiotemporal insights are invaluable for future urban planning and potential revisions to the city's master plan. The gathered data will enhance the existing database on LULC changes, facilitating comparative analysis and informing forthcoming legislation related to land use in Islamabad.

2. MATERIALS AND METHODS

2.1. Study area: geographic, demographic, and economic characteristics

Islamabad, Pakistan's capital, was intentionally designed in the early 1960s to serve as the new capital, replacing Karachi. It stands as the nation's sole modern, intricately planned city. According to the 2017 census, Islamabad covers an area of 906 km^2 and is inhabited by approximately 1.7 million residents, resulting in a population density of 1,876 people per km^2. The research site is located within the Potohar Plateau's topography, with elevations ranging from 457 to 610 m above sea level (asl). At different altitudes, there are distinct ecological features – tropical evergreen broadleaf forests at lower altitudes and subtropical evergreen coniferous and deciduous broadleaf woods at higher altitudes (Khan *et al.* 2011). The expansion of new housing projects and population growth has led to the removal of many of these trees (Khalid *et al.* 2021). The region experiences two primary growing seasons: from February to October for summer crops and from October to April for winter crops (Rehman *et al.* 2015).

When the construction of Islamabad commenced in the early 1960s, most of the area consisted of agricultural farms, open ground, and natural vegetation. In 1960, Islamabad's total population was merely 45,400 people, which gradually increased to 70,000 in 1970 and 189,300 in 1980. However, the city's population experienced rapid growth, reaching 342,900 in 1990, 568,700 in 2000, 804,000 in 2010, and 1.1 million in 2020. Over the past decade, the city's population has grown at an average rate of 3.7%. When considering the 0.90 million people residing in rural areas, the Islamabad district has a total population of 2 million. Most of the population is employed in the public and private sectors, with a relatively smaller presence in the business sector.

Islamabad's urban growth trends can be categorized into four primary types: village sprawl and leapfrog expansion, planning expansion, fringe sprawl and infilling, and merger. Village sprawl results from uncontrolled and unplanned leapfrog growth in Islamabad's suburbs. Changes in the city's demographics have led to revisions of the city's master plan, resulting in the second phase of urban sprawl. The third pattern of urban growth involves the extension of peri-urban districts toward the city's core. The fourth urban pattern, merger, occurs at the borders of Islamabad and Rawalpindi, two neighboring cities (Shah *et al.* 2022).

A significant portion of Islamabad's population is employed in public and private sector jobs, while the city has experienced substantial growth in economic and industrial activities. The Islamabad Capital Territory (ICT) comprises five zones, with the rural periphery and Zones I, II, and V designated as National Parks. The city's major industries encompass marble, chemical plants, steel mills, flour mills, oil paints, and pharmaceuticals. The city has been adhering to the 1992 Zoning Regulations. However, like other master plans, the Islamabad Master Plan has influenced urban growth and sometimes constrained economic activities. In recent times, many cities have been moving away from rigid master plans, increasingly allowing market forces and investor-driven initiatives to shape the types of buildings and developments in urban areas (Javid & Iqbal 2008).

The study area experiences a unique variant of a humid subtropical climate characterized by hot and humid summers, followed by a monsoon season and cool winters. The capital receives an average annual rainfall of 1,143 mm, with humidity levels averaging around 55%. The yearly climate averages include a maximum temperature of 28.5 °C and a minimum temperature of 14.1 °C. The study area, as illustrated in Figure 1, delineates the geographical expanse of the research area, encompassing all five designated zones.

2.2. Remote sensing data

Landsat 5 MSS (Vogelmann *et al.* 2001), Landsat 4–5 TM (Egorov *et al.* 2019), Landsat 7 ETM+ (Choate *et al.* 2021), and Landsat 8 OLI/TIRS (Ji *et al.* 2015) were employed for the assessment of LULC, NDVI, and normalized difference built-up index (NDBI) variations within the study area across the years 1980, 1995, 2010, and 2023. The data were sourced from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). Specific details about the acquired satellite images are provided in Figure 1.

2.3. Field survey data collection

Collecting field survey data is essential for validating and complementing RS information. In this study, 755 respondents, aged between 25 and 70 years, were chosen to provide crucial ground-truth data related to climate change parameters, with a specific focus on LULC changes. To ensure a representative sample, 25 out of the 50 union councils (https://ecp.gov.pk/)

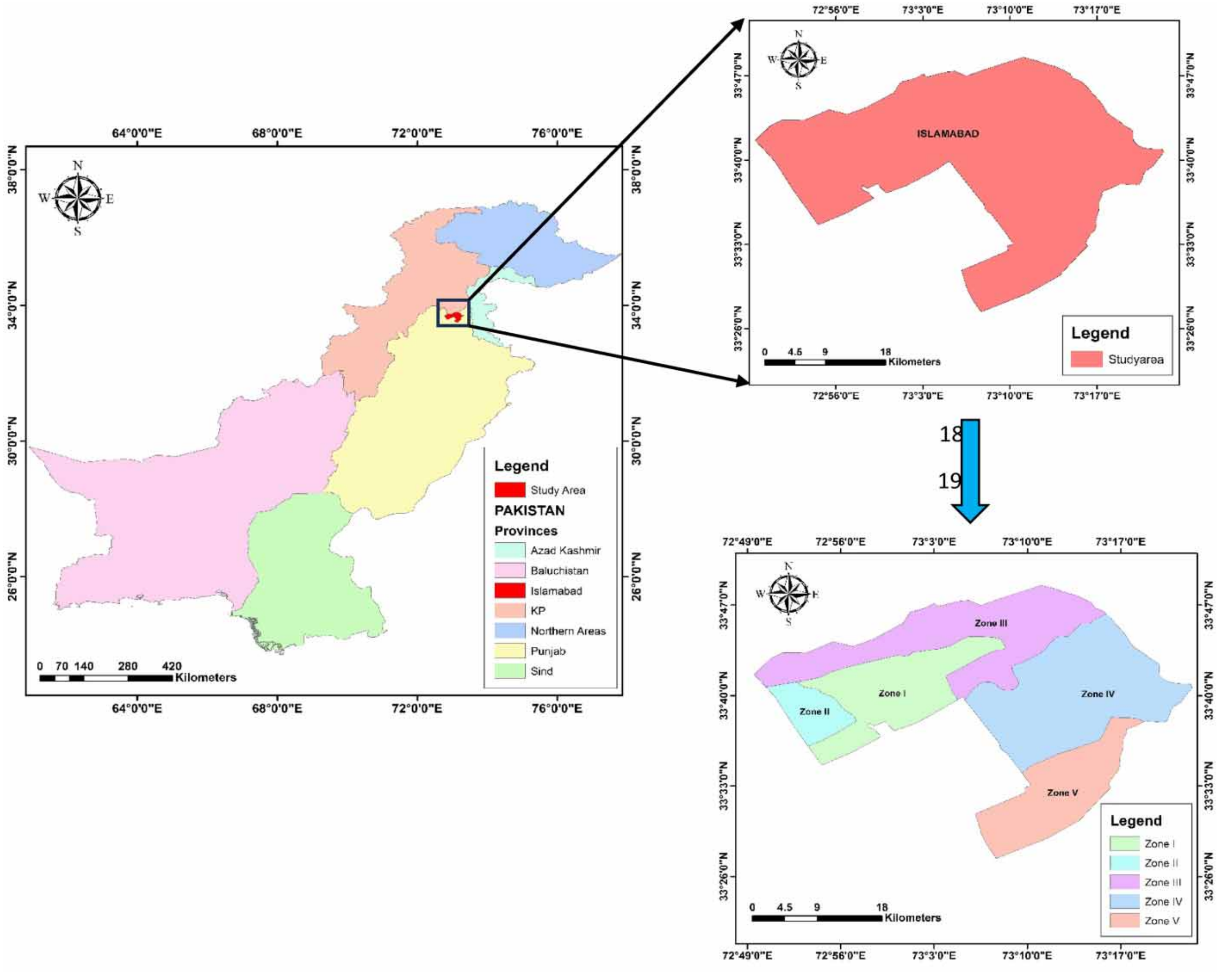

Figure 1 | Geographic extent of the study area with designated zones.

in the capital city were randomly chosen from various sectors, including urban, rural, industrial, and education. Each respondent's perspective was documented, and their inputs were linked to variables such as rainfall intensity, temperature variations, and changes in LULC over the past four decades. This comprehensive approach facilitates a deeper understanding of the complex interactions between climate change and land use changes in the study area.

2.4. Image compositing, and land use land cover classification

Landsat MSS imagery typically consists of four spectral bands. TM imagery from Landsat 4–5 is composed of a total of seven bands, ETM+ imagery from Landsat 7 encompasses eight bands, and Landsat 8 OLI/TIRS imagery offers a total of 11 bands. Landsat images consist of multiple bands, and to create single-color images and focus on specific study areas, these bands were composited. The compositing process was performed using ArcGIS 10.8. For the classification of digital LULC, the supervised image classification method was employed (Kumari 2014; Pareta 2014), with field data serving as the ground-truth data. The LULC maps for the selected temporal intervals were generated through supervised classification, emphasizing field validation alongside the training and validation stages. Subsequently, ArcGIS 10.8 was used to reclassify the LULC images, enabling the quantification of variations in land cover across the specified research years. The research framework is presented in Figure 2.

2.5. Evaluation of NDVI and NDBI

RS is a valuable tool for assessing vegetation health, with the NDVI being a widely used metric (Tariq *et al.* 2022). NDVI relies on measuring light reflectance in visible and near-infrared (NIR) wavelengths to gauge vegetation vitality. It finds applications in diverse fields, such as agriculture, forestry, and ecology, to monitor plant health, stress, and growth. NDVI provides insights into classifying various vegetation types, tracking changes in plant condition over time, and assessing overall vegetation cover. The NDVI computation is based on the principle that healthy green vegetation absorbs visible light and reflects NIR light, resulting in distinct reflectance patterns (Lunetta *et al.* 2006). It involves subtracting NIR reflectance from red reflectance and then dividing the result by the sum of NIR and red reflectance values. NDVI values typically range from -1 to 1. Values closer to 1 indicate lush and abundant vegetation, while negative values represent nonvegetated areas, and 0 corresponds to bare soil or water bodies (Aburas *et al.* 2015). NDVI can be calculated from Equation (1):

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

In this context, NIR represents the NIR radiation band (MSS and TM band 4; OLI and ETM band 5), while RED denotes the red radiation band (MSS band 2; TM band 3; OLI and ETM band 4).

NDBI, akin to NDVI, capitalizes on the assessment of light reflectance, although it operates in the shortwave-infrared and near-infrared (SWIR/NIR) spectral ranges. This metric finds extensive application across various domains, including urban planning and land use studies, to identify built-up areas and impervious surfaces, as well as assess changes in urban landscapes (Lin *et al.* 2015). NDBI computation follows a similar pattern, involving the subtraction of NIR reflectance from SWIR reflectance and then dividing by their summation. The computed NDBI values generally span from -1 to 1, with positive values indicating built-up regions and negative values signifying nonbuilt-up or natural areas (Ali *et al.* 2019). The NDBI can be derived using the formula presented in Equation (2):

$$\mathrm{NDBI} = \frac{\mathrm{SWIR} - \mathrm{NIR}}{\mathrm{SWIR} + \mathrm{NIR}} \tag{2}$$

where NIR is the near-infrared band (comprising MSS band 3, ETM and TM band 4, and OLI band 5) and SWIR is the central infrared band (comprising MSS band 4, TM and ETM band 5, and OLI band 6).

These spectral bands were employed to discern disparities within urbanized areas through satellite imagery. NDVI served the purpose of assessing alterations in vegetation cover, while NDBI was harnessed for a similar objective.

2.6. Image preprocessing and supervised image classification

Prior to engaging in change detection, it is imperative to undergo the preprocessing of satellite images, as this process helps establish a more immediate and coherent correlation between the acquired data and the underlying biophysical phenomena (Murmu *et al.* 2019). The satellite imagery utilized in the present study (shown in Table 1) was sourced from USGS Landsat

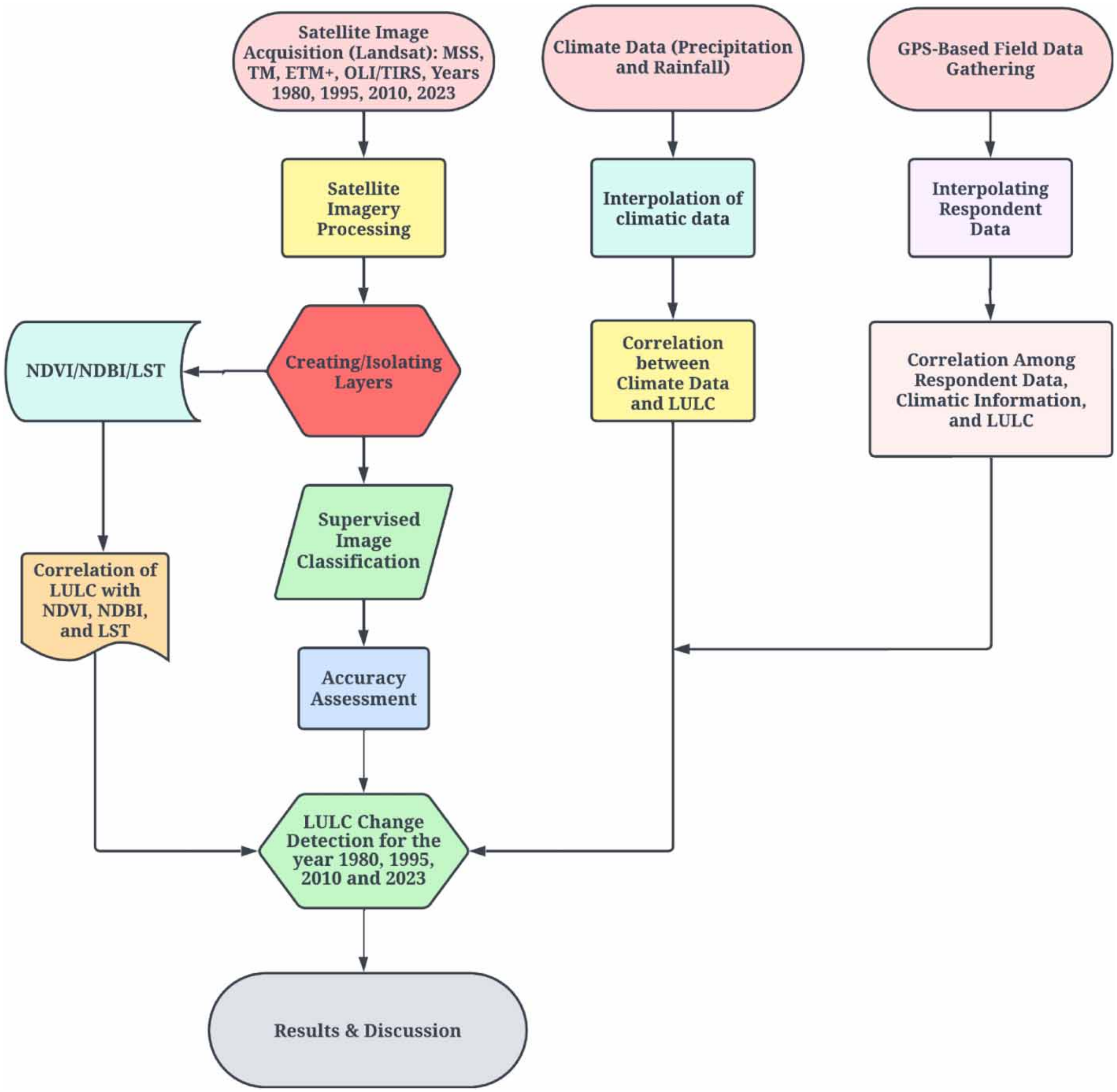

Figure 2 | Methodological approach for the current study.

data, which encompassed multiple bands, specifically ranging from band 1 to 7 (Irons *et al.* 2012). To standardize resolution across various Landsat products, we converted the coordinate systems of different imagery bands to the projected coordinate system of the study area. This conversion ensured a consistent cell size, achieving a uniform resolution for all satellite imagery utilized. These individual bands were meticulously imported into ArcMap GIS 10.8, where a critical step involved their composition. This was achieved through the employment of the 'Composite Band processing tool' within the Data Management tab. This comprehensive preprocessing ensures the data are well prepared for subsequent analysis and enhances the accuracy and relevance of land cover mapping, all in alignment with established best practices in the field. For detailed satellite imagery analysis, per-pixel signatures were meticulously assigned, segmenting the land area into five distinct categories: built-up regions, agricultural zones, forested areas, water bodies, and barren landscapes. Each class was endowed with a unique identity, accompanied by a distinct color scheme to facilitate clear differentiation. Training samples were thoughtfully selected for each land cover or land use type by outlining polygonal boundaries around representative areas. The pixel information contained within these polygons was employed to capture the spectral signatures corresponding to the different land cover

Table 1 | Details of employed satellite imagery

S. No	Accessed date	RS data type	Resolution (m)	Sensors	Path/rows
1	05/01/1980	Satellite imagery	60	MSS	150/037
2	10/01/1995	Satellite imagery	30	TM	150/037
3	07/01/2010	Satellite imagery	30	ETM +	150/037
4	25/01/2023	Satellite imagery	30	OLI/TIRS	150/037

categories as extracted from the satellite imagery. Following the preprocessing stage, a supervised image classification technique using the maximum likelihood method was employed (Xin & Wang 2019). This image classification approach empowers the analyst with significant control, enabling the meticulous selection of pixels that faithfully represent the desired target classes, thereby ensuring the precision of the classification results. In accordance with Gao & Liu (2010) guidance, the use of robust spectral signatures significantly reduces confusion in mapping the various land cover categories. Table 2 displays the five distinct landcover types, along with a detailed description for each class.

2.7. Accuracy assessment

Accuracy plays a crucial role in assessing the degree to which different image processing techniques align with the imagery (Lin *et al.* 2015; Zhang *et al.* 2016). The confusion matrix, as part of a broader accuracy assessment, holds significant relevance for evaluating current accuracy. This assessment involves various statistical methods, one of which is the percentage for producers' accuracy or workers' accuracy (Rahman *et al.* 2021). The overall accuracy, consumer accuracy, producer accuracy, and Kappa statistics are all provided by the confusion matrix. The consumers' and producers' accuracy measures serve as indicators of the dependability of a particular land cover category in satellite-generated classified imagery. They provide insight into the accuracy and fidelity of the data for each landcover type separately, as shown in Equations (3) and (4). These metrics collectively measure the error introduced by chance and provide valuable insights into the overall accuracy of the classification, which can be found from Equation (5). To ensure that classification data are effectively utilized in change detection, it is imperative to conduct accuracy assessments for individual classifications. Statistical analysis, including error matrices and nonparametric Kappa tests, was carried out to comprehensively evaluate the extent of classification accuracy. The Kappa test, in particular, accounts for all elements in the confusion matrix, not limited just to diagonal elements, making it a robust measure of classification accuracy (Rahman *et al.* 2017). The Kappa (K) value can be derived from Equation (6).

$$\text{Consumer accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (the row total)}} \tag{3}$$

$$\text{Producer accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (the column total)}} \tag{4}$$

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixels (diagonal)}}{\text{Total number of reference pixels}} \tag{5}$$

Table 2 | Landcover types along with descriptions

S. No	Landcover type	Description
1	Built-up area	Dwellings, business establishments, manufacturing, civic facilities, etc.
2	Agricultural land	Agricultural fields, plant nurseries, horticultural farms, and various other crops
3	Forests	All type of forest covers, dense tree regions
4	Bare lands	Areas devoid of any plant cover, uncultivated soil, and bare rock surfaces
5	Water bodies	Bodies of water, creeks, reservoirs, and aquatic channels

$$K = \frac{(\text{TS} \times \text{TCS}) - \sum(\text{Column total} \times \text{Row total})}{\text{TS}^2 - \sum(\text{Column total} - \text{Row total})} \quad (6)$$

where TS is the total sample and TCS is the total corrected samples.

2.8. LST correlation with LULC

The measurement of the earth's heat that can be felt to the touch is known as land surface temperature (LST) or earth skin temperature (Hulley *et al.* 2019). The swift pace of urbanization has brought about a significant metamorphosis in LULC, exerting influence on local and regional temperatures, ecological functions, and biodiversity. The escalation of LST in urban areas is predominantly attributed to poorly planned developments and unregulated alterations in LULC (Kafy *et al.* 2021; Abdullah *et al.* 2022). In this study, the correlation between LULC and LST is comprehensively elucidated, accompanied by visual representations in the results section. The discussion thoroughly explores the impact of LULC on LST and delineates its trend over the past four decades.

The LST values were estimated by utilizing thermal bands, extracted from the TM, TM Plus (TM+), and OLI datasets (Sekertekin & Bonafoni 2020). For Landsat 5 and Landsat 7, the designated thermal band is Band 6, covering the spectral range of 10.40 to 12.50 μm. In the case of Landsat 8 and 9, Band 10, with a spectral range of 10.6–11.19 μm, is employed for similar measurements. These bands are instrumental in quantifying the temperature of the Earth's surface (Zhang *et al.* 2021).

Initially, for Landsat 5 and Landsat 7, Equation (7) was applied to convert digital numbers (DNs) into radiance, while for Landsat 8 and Landsat 9, Equation (8) was utilized in this transformation process:

$$L_\lambda = \left(\frac{L_{\max\lambda} - L_{\min\lambda}}{\text{QCal}_{\max} - \text{QCal}_{\min}}\right) \times (\text{QCal} - \text{QCal}_{\min}) + L_{\min\lambda} \quad (7)$$

where L_λ = radiance detected by the sensor, $L_{\max\lambda}$ = Band 6 maximum radiance, $L_{\min\lambda}$ = Band 6 minimum radiance, QCal = calibrated pixel quantization in DN, $\text{QCal}_{\max}$ = maximum calibrated pixel quantization in DN, and $\text{QCal}_{\min}$ = minimum calibrated pixel quantization in DN.

$$L_\lambda = M_\text{L} \times \text{QCal} + A_\text{L} \quad (8)$$

where M_L = radiance scaling multiplier, A_L = radiance additive scaling multiplier, and QCal = calibrated pixel quantization in DN.

Following the DN transformation, the resulting brightness temperature (BT) in degrees Celsius is calculated using Equation (9):

$$\text{BT} = \left(\frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}\right) - 273.15 \quad (9)$$

where K_1 and K_2 represent the thermal band calibration constants, respectively.

LST is calculated by employing Equation (10):

$$\text{LST} = \left(\frac{\text{BT}}{1 + \left(\frac{\lambda \times \text{BT}}{\rho}\right)}\right) \times \ln(\varepsilon) \quad (10)$$

where λ and ρ are constants, obtained from the meta-data file provided by USGS along with the Landsat imagery (MLT text file), and ε is the emissivity obtained from Equation (11):

$$\varepsilon = 0.004 \times M_\text{v} + 0.986 \quad (11)$$

P_v is the proportion of vegetation, which can be obtained from Equation (12):

$$P_v = \left(\frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}}\right)^2 \quad (12)$$

where NDVI was already estimated from Equation (1).

3. RESULTS AND DISCUSSION

3.1. Respondents' perception on climate change linked to LULC

Perceptions of climate variability and its connection to LULC were gathered through a comprehensive survey. A significant majority, accounting for 91.5% of the respondents, conveyed their views on climate change. They highlighted the tangible impacts of climate change on the capital city, ranging from intensified rainfall, occurrences of extreme weather events, to fluctuations in temperature. This encompassed both the frigidity of winters and the sweltering heat of summers. The respondents' perspectives are vividly depicted in Figure 3, illustrating their assessment of climate change intensity, whether it falls within the spectrum of extremity, mildness, or an intermediate state.

Of those 755 individuals surveyed, 50.21% reported substantial fluctuations in rainfall volume and intensity. These changes manifested in irregular drought periods and uncharacteristic temperature oscillations. Reports from various regions of Pakistan corroborate the trend of decreasing rainfall and deteriorating drought conditions (Prestele *et al.* 2016; Gao *et al.* 2020). An additional 18.37% acknowledged the significance of these variations, while 12.27%, 10.67%, and 8.5% expressed perceptions of moderate, slight, and stable climatic fluctuations, respectively. It is noteworthy that most respondents observed an escalation in rainfall intensity coupled with a decrease in volume and the frequency of wet days, resulting in recurring flood-related damages.

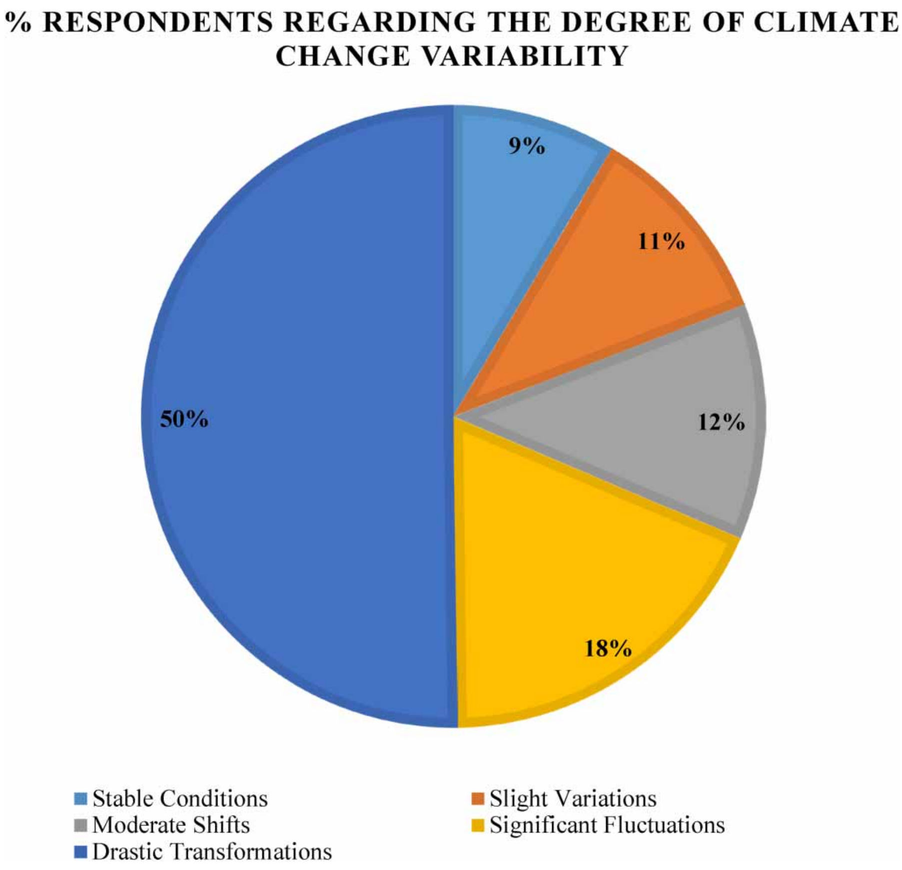

Figure 3 | Respondent views on climate change intensity.

The feedback provided by the respondents was also scrupulously recorded for three key climatic variables: LULC changes, temperature fluctuations, and rainfall patterns. The outcomes of this assessment are comprehensively detailed in Table 3. The percentages reveal significant variations in all three climatic factors, with LULC changes exhibiting the most pronounced impact.

3.2. Assessing land cover transformations and urban expansion

To assess the most pronounced relative fluctuations in LULC over the preceding four decades within the designated research area, an exhaustive evaluation of LULC types was conducted exhibiting both the most substantial and the least significant alterations in the respective LULC profiles. Table 4 presents the results of the comprehensive comparative analysis, delineating the proportion of each landcover type in relation to the total expanse of the study region for the entirety of four decades. Figures 4 and 5 visually illustrate the significant transformations in the LULC of Islamabad from the year 1980 to 2023.

3.2.1. Alterations in land cover within built-up areas

From 1980 to 1995, the urbanized expanse of Islamabad underwent an increment of 59.48%, marked by an average annual growth rate of 3.96%. This trend endured through the subsequent period from 1995 to 2010, revealing a 46.4% expansion over the course of 15 years, characterized by an average increase of 3.09% per annum. Furthermore, the urbanized territory exhibited a significant surge of 48.10% between 2010 and 2023, sustaining an average annual growth rate of 3.70%. The cumulative growth by the conclusion of this four-decade span marks an astonishing 246% increase compared with the initial conditions. The surge in urbanization experienced by Islamabad during this decade can be attributed to a confluence of factors, which are linked to internal migration and the substantial development of housing complexes by private societies. This influx of individuals from various regions of the country can be partly attributed to the displacement of internally displaced persons, a consequence of the escalation in terrorism-related activities nationwide. Simultaneously, the government's introduction of lucrative incentives for developers within the housing industry played a pivotal role in fostering this urbanization trend. The presence of affordable land in the city's suburban areas further facilitated these developers in acquiring the necessary plots for their ventures. Consequently, this amalgamation of factors precipitated a significant upswing in construction activity.

Table 3 | Climatic-variable assessment results

S. No	Climatic variables	Feedback	% Respondents
1	LULC change	Yes	94.5
		No	5.5
2	Temperature variation	Positive change	85
		No change	0
		Negative change	15
3	Rainfall variability	Heavy rainfall	23
		Consistency	68
		Reduced rainfall	9

Table 4 | Diverse land use and landcover types, and their transformations from 1980 to 2019

		1980		1995		2010		2023	
S. No	Landcover type	km²	%	km²	%	km²	%	km²	%
1	Built-up area	159.7	17.6	254.7	28.1	372.9	41.1	552.3	61.0
2	Agricultural land	228.2	25.2	320.9	35.4	295.8	32.7	151	16.6
3	Forest cover	148.9	16.4	94.6	10.4	84.7	9.4	151.6	16.7
4	Water bodies	9.7	1.1	6.6	0.7	5.9	0.7	4.9	0.5
5	Bare land	359.5	39.7	229.2	25.3	146.8	16.2	46.2	5.1
	Total	906	100	906	100	906	100	906	100

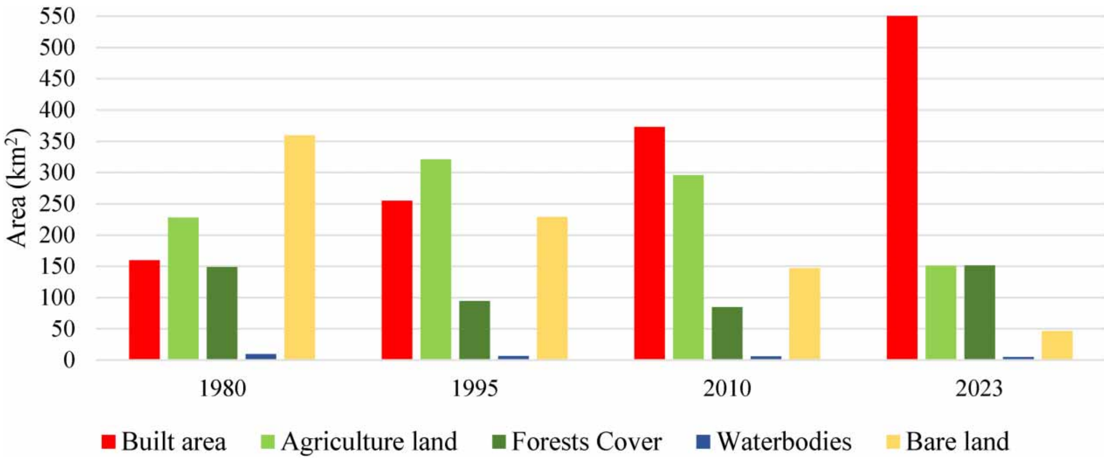

Figure 4 | Transformations in the land use and land cover of Islamabad from 1980 to 2023.

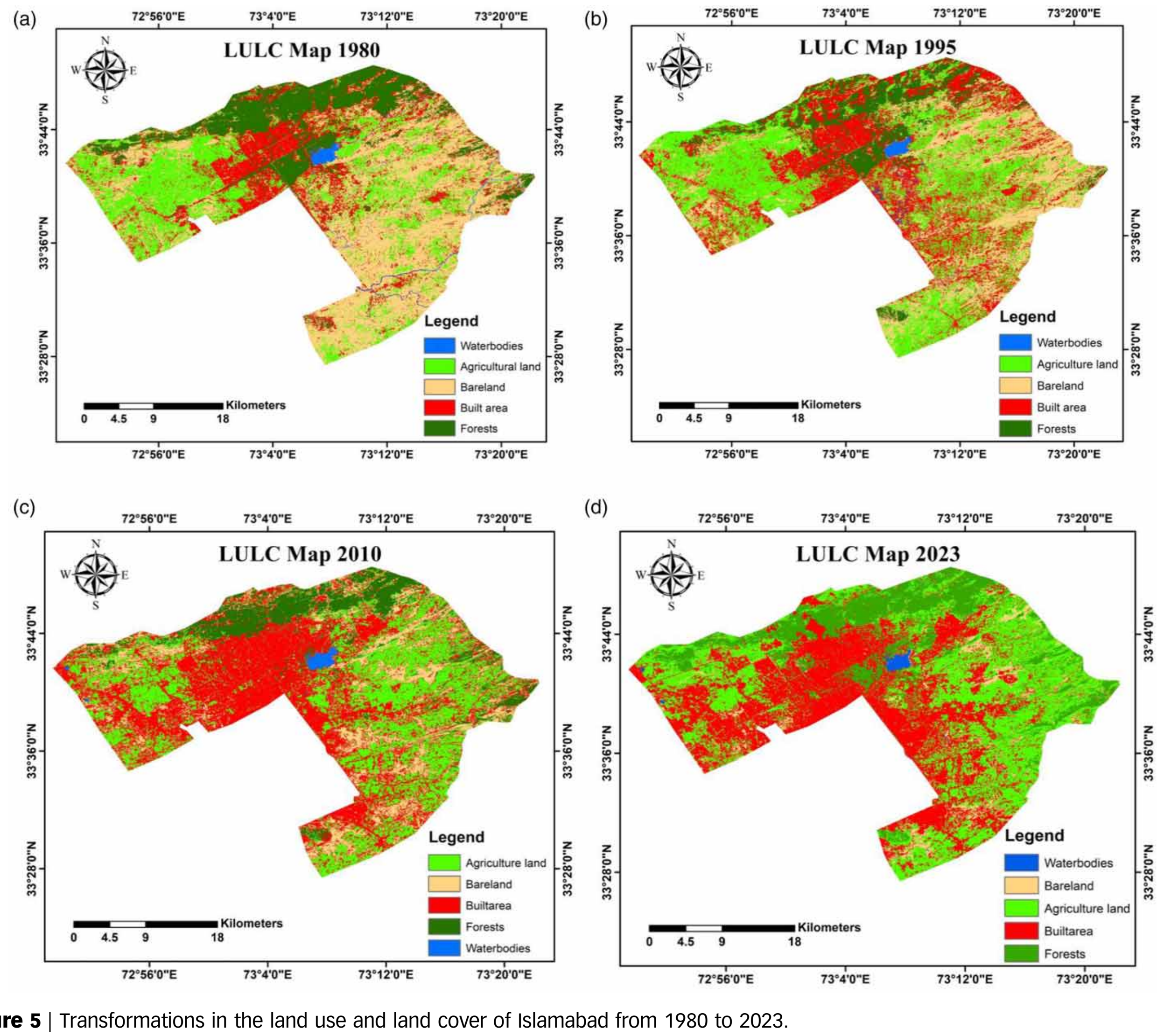

Figure 5 | Transformations in the land use and land cover of Islamabad from 1980 to 2023.

However, it is worth noting that the overall growth in construction activity has soared to an impressive 60.96% between 1980 and 2023. This figure indicates that Islamabad has nearly reached its carrying capacity as over half of the city's total land area has been dedicated to the construction of buildings and associated physical infrastructure. Islamabad's pronounced urbanization trajectory is intricately connected to the unchecked and swift expansion of the city's peripheries. The Capital Development Authority (CDA) bears a significant share of responsibility for the inadequacies in urban planning within the city. This shortfall has fostered an environment wherein private developers have made substantial investments in housing ventures, encompassing both authorized and unauthorized areas of the city. The outcome of this urban conflict has engendered a multitude of concerns, including but not limited to issues surrounding housing quality and affordability, challenges related to the provision of clean drinking water and sanitation, as well as complications pertaining to transportation and mobility (Nishtar *et al.* 2014). The progressive transformation of the urbanized region is visually depicted in Figures 4 and 5.

3.2.2. Transformations in land cover within agricultural areas

The expansion of arable lands in peri-urban regions, attributed to the diligent efforts of local farmers, has led to a noticeable increase in agricultural coverage. A significant contribution to this expanded agricultural landscape has come from Afghan immigrants residing in the suburbs of Islamabad. Consequently, the city has witnessed an augmentation in its agricultural output, particularly during the time span from 1980 to 1995, when agricultural land experienced a substantial rise of 40.62%. However, the dynamic urbanization trends characterizing the city and the ongoing development of unsustainable housing projects, stemming from the CDA's inadequate management, have precipitated a noteworthy decline in the percentage of agricultural land. This decrease has amounted to 52.94% from 1995 to 2023. Another key element influencing this shift is the insufficiency of government incentives for crop production. This lack of support has compelled farmers to consider alternative uses for their land, thus diverting them away from agricultural pursuits. Table 4 presents the proportion of agricultural land in relation to the total area of Islamabad for the past four decades.

3.2.3. Alterations in land cover within forested areas

The primary concern in Islamabad has revolved around the persistent issue of deforestation, which has resulted in a consistent decline in woodland coverage over two significant time periods: from 1980 to 1995, a substantial decrease of 36.47%, and from 1995 to 2010, a further decline of 10.46%. This decline in forested areas can be closely correlated with the concurrent expansion of new infrastructure and housing projects within the city. The augmentation of built-up areas can be directly attributed to the reduction in forest cover. In the period between 1980 and 2010, substantial tracts of forested lands in Islamabad were cleared to make way for the construction of new highways and avenues. This marked transition has not only had adverse implications for the city's environmental equilibrium but also places the local climate in a precarious and perilous predicament. The shift in the trend observed between 2010 and 2013 was notable, particularly with respect to the capital city's forest cover. During this period, there was a substantial increase in the forested area, expanding from 84.67 km^2 in 2010 to 151 km^2 in 2023, representing a remarkable 78.34% surge. This remarkable positive transformation can be attributed to the Ten Billion Tree Tsunami (TBTT) Plantation Project, a conservation initiative spearheaded by the government of that time. This project implemented rigorous regulations and stringent measures aimed at curbing deforestation while concurrently nurturing and enhancing forested regions throughout the nation, with a particular emphasis on the capital city. The CDA played a pivotal role in the successful execution of this reforestation project, working hand in hand with the government. Their involvement was particularly significant as previous deforestation was partially attributed to their negligence. This collaborative effort between the government and the CDA not only reversed the adverse trend but also contributed significantly to the remarkable increase in forest cover witnessed in the capital city during this period. The trend of forest cover change is shown in Figures 4 and 5.

3.2.4. Alterations in land use and water bodies

Over the course of several decades, there has been a marked reduction in the extent of land covered by water bodies in the region, with a substantial decrease from 9.717 to 4.923 km^2. This decline is notable, with specific reductions of 32.48%, 10.6%, and 16.9% occurring between the intervals of 1980 to 1995, 1995 to 2010, and 2010 to 2023, respectively. The underlying causes of this shift can be primarily attributed to urban sprawl and the extensive development of new infrastructure within the area. These factors have brought about significant alterations in the availability of water resources and the process of underground-water recharging. Notably, the depth at which underground water can be accessed has increased across most areas, with some locations seeing a shift from shallow depths to depths exceeding 60 metres. Because of these transformative changes, one of the most pressing challenges faced by the municipal authorities of the city over the past two decades has been the availability and supply of safe drinking water. This critical issue underscores the need for a comprehensive approach to address the growing demand for clean and accessible water resources within the urban landscape. The reduction in water bodies can be confirmed by Table 4.

3.2.5. Transformations in land cover within arid regions

The expanse of barren land has witnessed a substantial reduction over several decades, with a transformation from 359.50 km^2 in 1980 to 229.2 km^2 in 1995, signifying a considerable decrease of 36.24%. This decline continued in the subsequent years, as from 1995 to 2010, the barren land area further contracted to 146.76 km^2, constituting a 35.9% reduction. Most recently, from 2010 to 2023, the barren land area diminished to a mere 46.15 km^2, marking a significant decrease of 68.53%. The expansion of built-up areas, which has encroached upon not only forested regions but also water bodies, has played a substantial role in the loss of arid terrain. Nevertheless, it is essential to note that during the period coinciding with the capital's comprehensive reforestation endeavor, some of the previously barren land was converted into thriving forest cover. Simultaneously, a portion of the erstwhile barren terrain was repurposed for agricultural cultivation, further illustrating the dynamic and multifaceted nature of these land cover changes.

3.3. NDVI and NDBI analysis of Islamabad's land cover

The NDVI is a quantitative measure of vegetation health, with high NDVI values indicating lush growth and low values suggesting sparse plant cover. An examination of NDVI standards in Islamabad Capital Territory over the years reveals substantial fluctuations. In 1980, NDVI ranged from $+0.4523$ to -0.0856. By 1995, this span shifted to $+0.3917$ to -0.2221. In 2010, NDVI ranged from -0.0974 to $+0.1596$, while in 2023, it varied from -0.0702 to $+0.4422$. A distinct pattern emerges, with NDVI declining from 1980 to 2010 but rebounding from 2010 to 2023. This resurgence reflects the positive impact of dedicated reforestation efforts, resulting in a remarkable 78.34% increase in forest cover, enhancing the region's green landscape. Figure 6 illustrates NDVI values spanning four decades.

Figure 7 provides insight into the spatial distribution of water bodies and urban development in 1980, 1995, 2010, and 2023 through NDBI categories. The maximum NDBI values for these years were $+0.1552$, $+0.1696$, $+0.5120$, and $+0.6031$, while the minimum values were -0.2348, -0.2221, -0.1805, and -0.3336, respectively. The increasing maximum NDBI values demonstrate the city's expanding infrastructure, which now covers more than half of the total land area, resulting in saturation within the region. Table 5 provides a comprehensive overview of both the highest and lowest NDVI and NDBI values for the duration of the four decades. Table 6 represents the NDVI and NDBI value ranges for each of the landcover types.

3.4. Accuracy assessment

The accuracy assessment of the land cover maps for the years 1980, 1995, 2010, and 2023 was conducted in ArcGIS 10.8. A total of 200 random assessment points were methodically generated for each land cover map, utilizing the 'Create Accuracy Assessment Points' feature within the 'Segmentation and Classification' tool in the ArcToolbox. Subsequently, the point layer was converted into a KML file through the conversion tools available in the ArcToolbox. All assessment points in the accuracy assessment layer underwent a rigorous validation process against ground-truth data, meticulously cross-referencing with corresponding satellite imagery in Google Earth within the same temporal domain. Following the validation and adjustment of the accuracy assessment layer in ArcGIS against the ground-truth data acquired from Google Earth, the 'Compute Confusion Matrix' tool was employed to generate an accuracy assessment matrix. This matrix provided essential metrics, including producers accuracy, consumers accuracy, and Kappa values, as shown in Table 7. The overall accuracy values were then extracted from the table generated in the preceding step. This comprehensive assessment ensured the reliability and precision of the land cover maps throughout the specified time periods.

The overall accuracy of the land cover classification for the years 1980, 1995, 2010, and 2023 is reported as 86.98%, 94.83%, 87.52%, and 93.28%, respectively. Furthermore, the Kappa (K) coefficients stand at 85.02, 89.45, 86.41, and 91.98 for the corresponding years. The Kappa scores, exceeding 85%, signify a high level of reliability in the classification process, demonstrating strong agreement between the classification results and the ground-truth data (Carletta 1996; Rwanga &

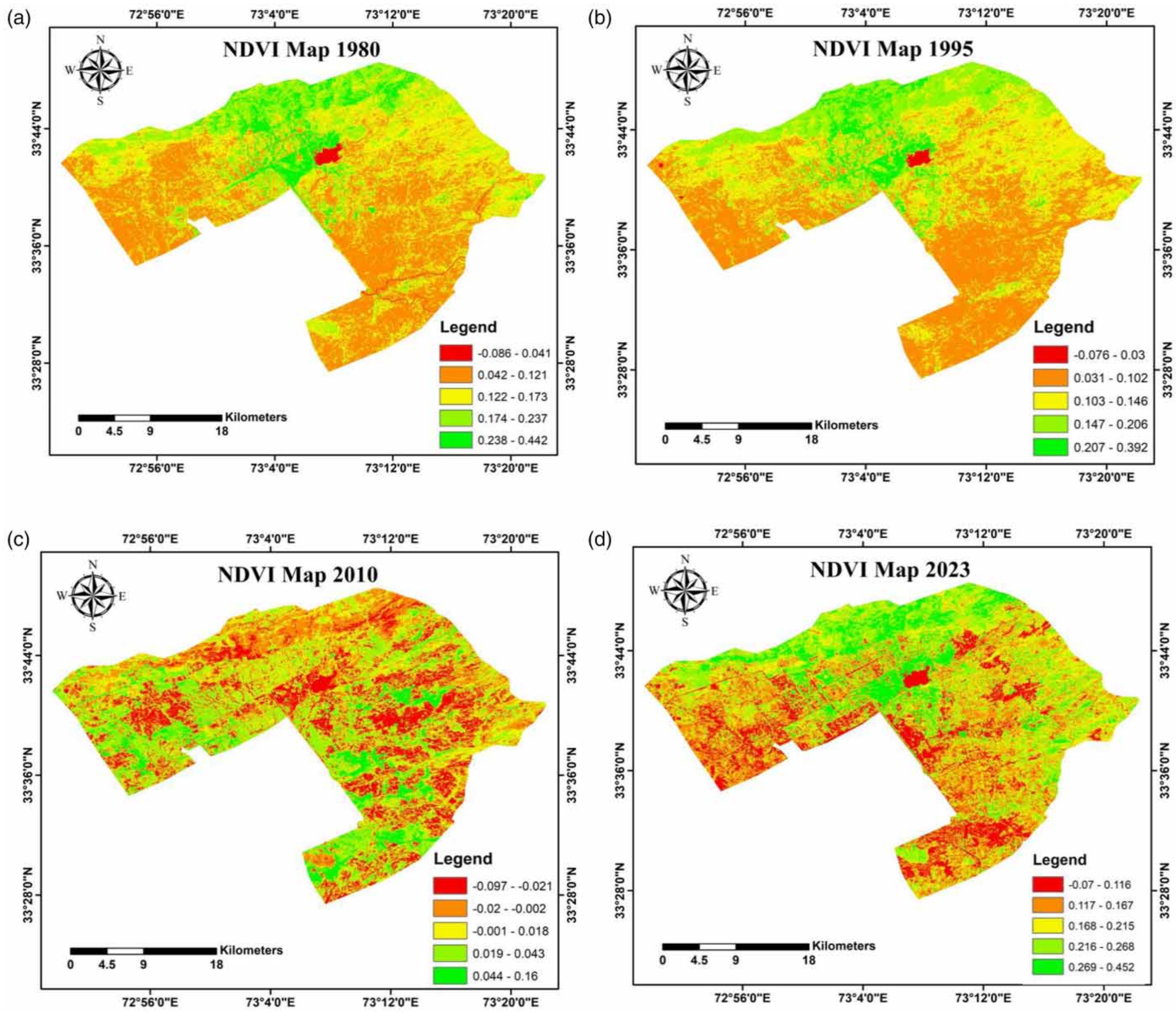

Figure 6 | NDVI trends over four decades in Islamabad: 1980–2023.

Ndambuki 2017; Foody 2020). Table 8 shows the Kappa value against the strength of agreement. This highlights the robustness of the classification findings and their consistency with the actual land cover conditions for each of the specified years.

3.5. Land surface temperature trends and variability across different land use categories

Landsat thermal bands were employed to assess the response of LST to changing LULC across various locations in the years 1980, 1995, 2010, and 2023. Utilizing the 'Zonal Statistics' tool within the ArcGIS 10.8 environment, the LULC and LST data were superimposed, generating statistical results for LST across different land use categories. The results are shown in Figures 8 and 9. The standard deviation of the LST of water bodies and undeveloped terrain was larger each year as shown in the figure, suggesting that there were significant and irregular variations in the LST of these two land use patterns inside the research area. This is mostly because bare land reacts swiftly to temperature changes and that water bodies have a greater capacity to absorb heat than other types of land cover. The findings reveal substantial spatial and temporal variations in LST across different land use categories from 1980 to 2023. The observed trend indicates that the average temperature follows the order: bare lands > built-up > agriculture > forest cover > water bodies. Built-up and bare land exhibited higher average LST compared with other land use types, while agricultural land, forest land, and water bodies consistently showed relatively lower average LST. In 1980, the average temperature ranged from 17 to 38 °C, increasing to 19–39 °C in

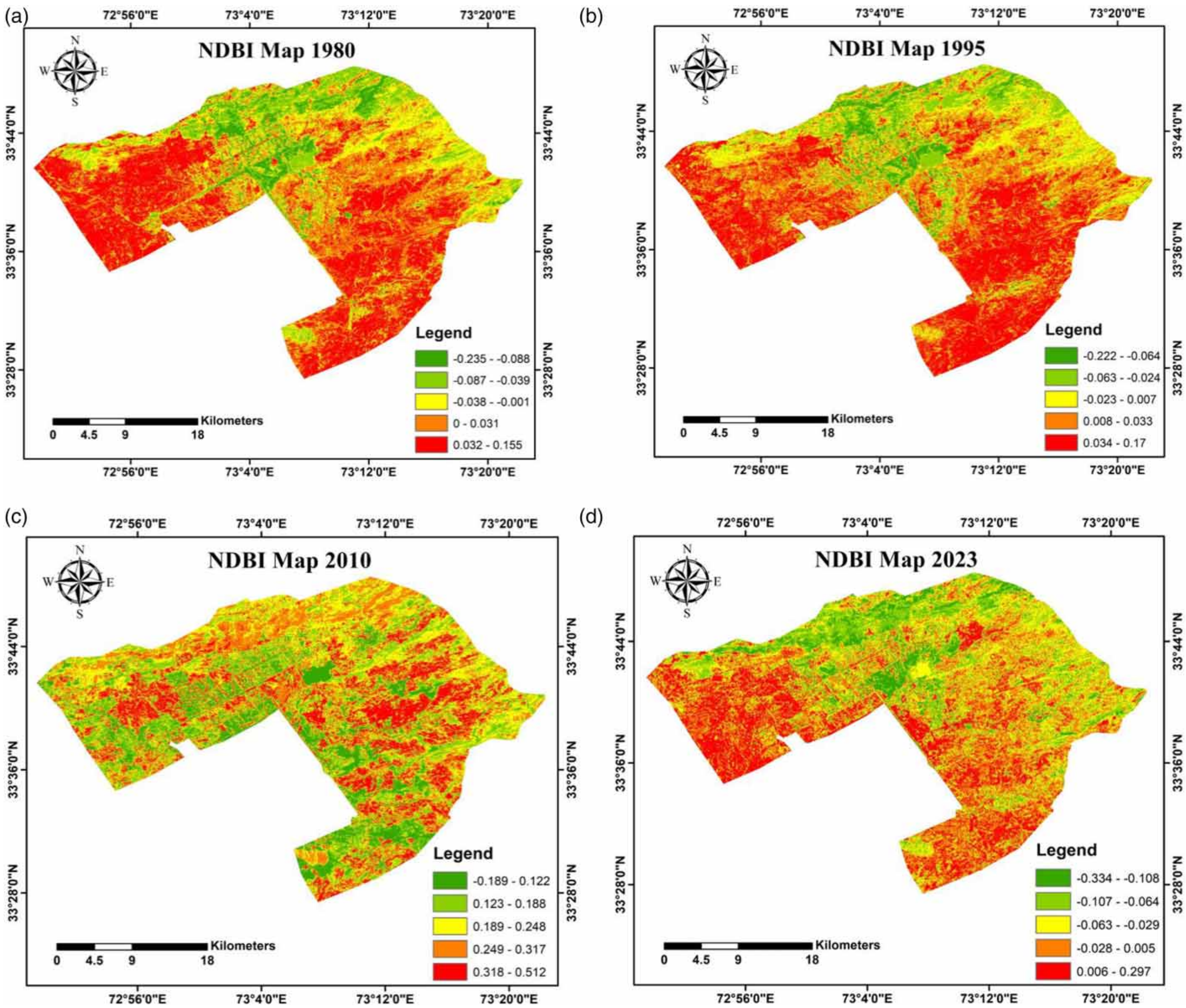

Figure 7 | NDBI trends over four decades in Islamabad: 1980–2023.

Table 5 | Overview of extremes in NDVI and NDBI values across four decades

		NDVI			NDBI		
S. No	**Year**	**Maximum**	**Minimum**	**Average**	**Maximum**	**Minimum**	**Average**
1	1980	0.4523	−0.0856	0.1833	0.1552	−0.2348	−0.0398
2	1995	0.3917	−0.2221	0.0848	0.1696	−0.2221	−0.02625
3	2010	0.1596	−0.0974	0.0311	0.512	−0.1805	0.16575
4	2023	0.4422	−0.0702	0.1860	0.6031	−0.3336	0.13475

1995 (an overall 2 °C rise) and further escalating to 20–41 °C in 2010 (with a 1 °C rise for the minimum temperature and 2 °C rise for the maximum). However, the temperature trend deviated from 2010 to 2023, with the temperature range stabilizing at 20–40 °C. This anomaly is attributed to the reforestation initiative undertaken in the capital city from 2015 to 2022, which increased forest cover and mitigated the average temperature rise. This highlights reforestation as an effective measure in addressing climate change. Figure 9 visually illustrates that the LST standard deviation of bare land and water bodies increased annually, indicating substantial and irregular variations in LST for these land use types within the research area.

Table 6 | Variation of NDVI and NDBI across landcover types

		NDVI			NDBI		
S. No	**LULC type**	**Maximum**	**Minimum**	**Average**	**Maximum**	**Minimum**	**Average**
1	Agriculture	0.375	0.198	0.286	0.200	−0.135	0.035
2	Forests	0.452	0.256	0.354	0.210	−0.315	−0.052
3	Water bodies	0.026	−0.097	−0.035	−0.064	−0.034	−0.049
4	Built-up area	0.329	0.234	0.281	0.512	0.318	0.415
5	Bare lands	0.204	0.122	0.163	0.435	0.185	0.310

Table 7 | Kappa accuracy of producers and consumers

	Producers accuracy (%) (P_Accuracy)					Consumers accuracy (%) (U_Accuracy)						
Year	**C1**	**C2**	**C3**	**C4**	**C5**	**C1**	**C2**	**C3**	**C4**	**C5**	**Overall accuracy**	**Kappa (*K*)**
1980	82.73	85.1	81.7	89.8	79.6	83.4	87.3	90.6	83.3	92.3	86.98	85.02
1995	92.5	100	89.8	88.7	91.6	94.6	90.5	96.1	89.7	100	94.83	89.45
2010	96.3	94.5	85.7	100	81.9	93.9	79.6	100	85.8	95.5	87.52	86.41
2023	93.2	95.6	100	89.4	94.8	88.3	93.8	91.2	98.4	100	93.28	91.98

C1 = agricultural land, C2 = bare land, C3 = built-up area, C4 = forests, C5 = water bodies.

Table 8 | Kappa accuracy assessment ranges (Rwanga & Ndambuki 2017)

S. No	Kappa statistics (%)	Strength of agreement
1	<0	Poor
2	0–20	Slight
3	21–40	Fair
4	41–60	Moderate
5	61–80	Substantial
6	81–100	Almost perfect

This phenomenon is attributed to the rapid responsiveness of bare land to temperature changes and the higher heat absorption capacity of water bodies compared with other landcover types. In addition, built-up areas and forest terrain consistently exhibited high- and low-temperature conditions, respectively, with a smaller standard deviation in LST.

3.6. Impacts of changes in land cover on the study area and its master plan

Islamabad has undergone a significant phase of urbanization, characterized by unsustainable alterations in land use, resulting in a range of challenges akin to those experienced in various urban centers across the country (Hussain 2017). This urban transition has led to a substantial increase in the annual mean temperature and a concurrent decrease in average annual rainfall. The compelling visual evidence presented through satellite imagery, contrasting the landscape in 1980 with that in 2023, underscores the evident expansion of Islamabad's urban footprint. This growth, however, has come at the expense of the utilization of water bodies and arid regions for commercial purposes, which includes deforestation. The relentless focus on urban development over the course of these four decades has pushed the city's capacity for growth to its limits (60.96% of the total area is now occupied by infrastructure). Consequently, the quality of life in the city continues to be challenged, reflecting the need for sustainable urban planning and resource management. The original master plan of Islamabad, crafted in the 1960s by M/S Doxiadis Associates (Doxiadis Associates – Home Page), a Greek firm, underwent modifications to accommodate

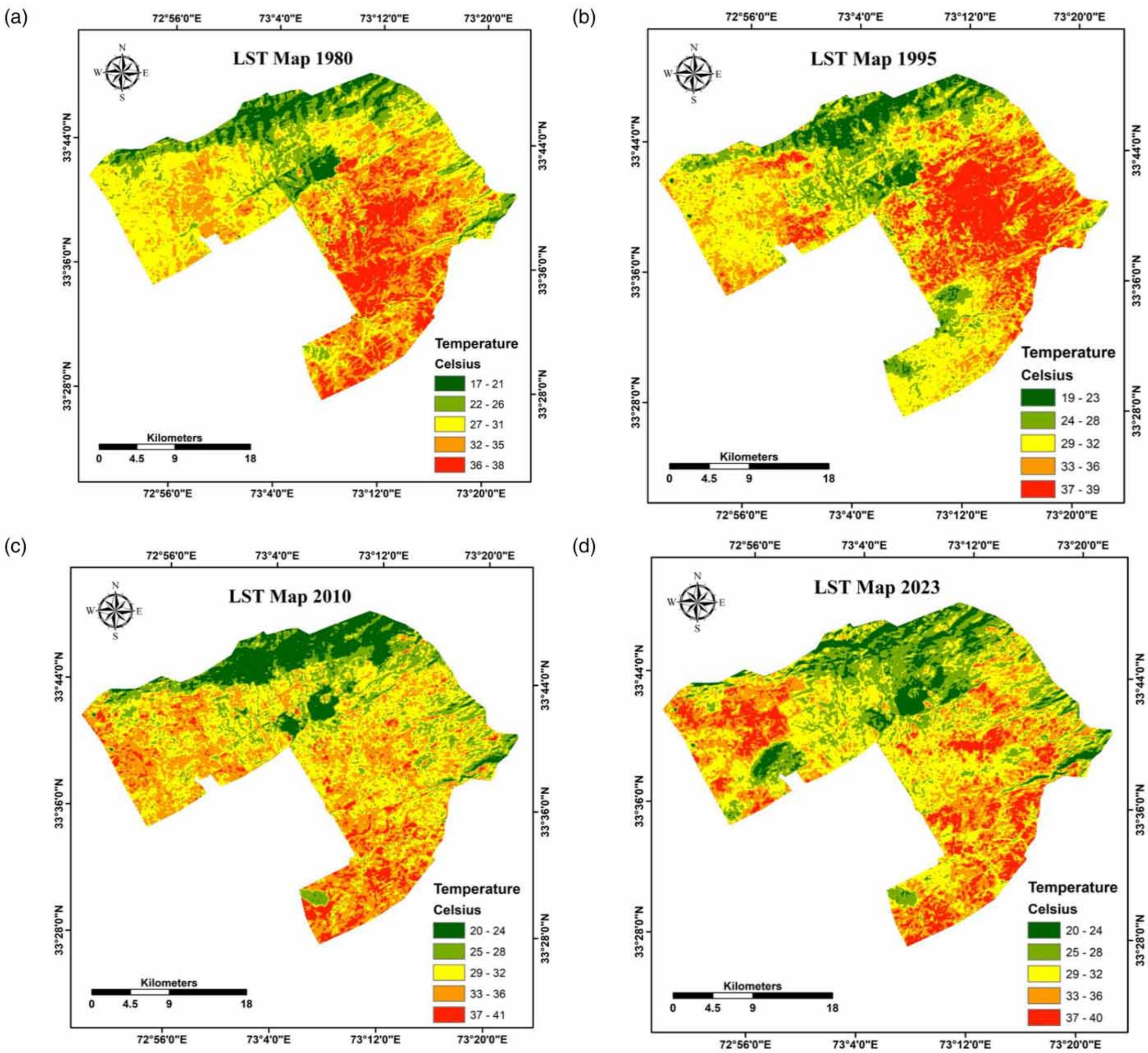

Figure 8 | LST trend over the last four decades in the study region.

evolving circumstances. Initially, the metropolitan area was delineated into three distinct segments: Islamabad, Islamabad National Park, and Rawalpindi Cantonment. The task of developing the new capital was entrusted to the CDA, with a mandate for periodic revisions every two decades to align with the changing physical and socioeconomic landscape. The inaugural revision in 1978 brought significant alterations, discontinuing the Industry and Trade (I&T) Zone while establishing the blue areas and allocating a substantial tract to military troops in sectors E-8, E-9, E-10, and D-10. Regrettably, subsequent governments did not undertake further revisions to the master plan. The enactment of the 1979 ICT Local Government Ordinance and the establishment of union councils in rural areas gave rise to unplanned and unapproved urban sprawl and housing societies in the city's outskirts. The Cabinet's Zoning Regulations were eventually accepted by the CDA, further dividing Zone-4 into four subzones (A–D) in 1992. In 2015, the Metropolitan Corporation, led by an elected mayor and union councils, was established. In response to a Supreme Court order, the Federal Government was compelled to address the regularization of irregular settlements, imposing fines and charges. The urban sprawl in Islamabad has necessitated the legalization of illegal constructions and unapproved development projects on the city's periphery, heightening its vulnerability to environmental degradation. The future Islamabad Master Plan Framework is underpinned by the following principles: the development of sustainable regional and urban planning concepts, the promotion of coordinated compact

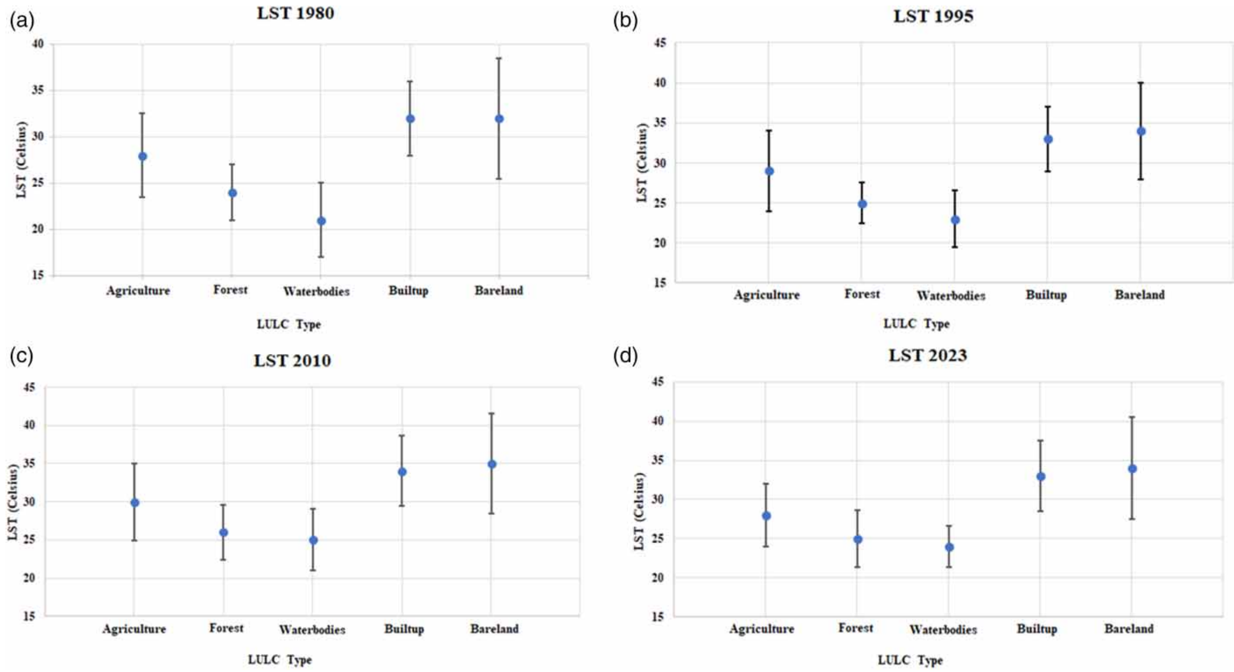

Figure 9 | Temporal variation in mean LSTs and standard deviations across different land use types (1980–2023).

development at all scales, and a commitment to implementation from inception. The CDA has proposed a series of plans, including the Long-Range Regional Plan (LRRP)-2050, the Framework for Islamabad–Rawalpindi Metropolitan Urban Plan (FIRMUP) 2050, and the Islamabad Master Plan (ISP) 2040. These regional plans are vital for safeguarding the capital from further environmental degradation, and the long-term master plan must meticulously incorporate the tenets of sustainable urban development. Prudent land management based on sustainable urban planning is imperative to avert further degradation of the city, which has persisted due to the negligence of relevant authorities.

4. CONCLUSIONS AND RECOMMENDATIONS

This study delves into the assessment of urban expansion within Islamabad, the capital city of Pakistan. The evaluation is conducted through an analysis of LULC changes, drawing insights from satellite imagery captured in four distinct epochs: 1980, 1995, 2010, and 2023. To facilitate this analysis, the land was categorized into five distinct classes, each representing specific land use types. These classes encompass agricultural lands, built-up areas, barren terrains, forested areas, and bodies of water. The study endeavors to comprehensively examine and interpret the shifts and transitions occurring within these land categories over the specified time frame.

The research outcomes can be succinctly summarized as follows:

Over the course of four decades, from 1980 to 2023, there has been a remarkable and concerning escalation in the built-up area, surging from 159.7 km^2, constituting 17.6% of the total land area, to an expanded coverage of 552.3 km^2, which now encompasses 60.96% of the landscape. This transformation reflects an inherently unsustainable trend primarily attributed to the proliferation of new housing developments and the emergence of unauthorized settlements, raising critical concerns for urban planning and management. During the initial phase from 1980 to 1995, the extent of agricultural land witnessed an increase, expanding from 228.2 to 320.9 km^2, marking a significant rise of 40.6%. However, the subsequent period from 1995 to 2023 saw a contrasting trajectory, with the agricultural land dwindling from 320.9 km^2 (constituting 35.4% of the total area) to 151 km^2 (comprising 16.6% of the landscape). This shift can be attributed to the pressures of urbanization and the challenges posed by the burgeoning urban population, underscoring the complexities of land use dynamics in response to urban growth and overcrowding. The expanse of forest land within the study area underwent a significant transformation during the interval spanning from 1980 to 2010. During this time, the forested area dwindled, plummeting from 148.9 km^2 (comprising 16.4% of the region) to 84.7 km^2 (constituting 9.4% of the landscape). This decline can be largely attributed to the deleterious consequences of deforestation and the concurrent development of new road networks and infrastructure throughout the city, as residents cleared substantial portions of forests to accommodate their housing needs. However, from 2010 to 2023, the scenario experienced a remarkable turnaround, witnessing an upsurge in forest cover to 151.6 km^2, equivalent to 16.7% of the total area. This positive shift can be chiefly attributed to the capital's robust reforestation initiative, which has played a pivotal role in reinstating and enhancing the region's green cover. The extent of land occupied by water bodies has undergone a significant reduction, diminishing from 9.7 km^2, representing 1.1% of the total area, to a mere 4.9 km^2, equivalent to 0.5%. This substantial decline has resulted in a depletion of the aquifer and has consequently imposed a critical water scarcity challenge upon the city, emphasizing the pressing need for sustainable water resource management and conservation efforts. Over the period spanning from 1980 to 2023, there has been a significant reduction in the expanse of arid terrain, decreasing from 359.5 km^2, accounting for 39.7% of the total land area, to 46.2 km^2, which now constitutes a mere 5.1%. This substantial transformation is partially attributed to the combined effects of expanded agricultural land and ongoing construction activities, which have effectively reclaimed and repurposed segments of this once desolate terrain for productive use and development.

The uncontrolled and unregulated land use alterations in Islamabad, Pakistan, witnessed from 1980 to 2023, have compelled city authorities to re-evaluate and revise the city's master plan. Simultaneously, the persistence of unauthorized construction and buildings has raised urgent concerns regarding the integrity of the city's ecosystem, placing it in a precarious state of jeopardy and demanding immediate attention and intervention for the preservation of its environmental balance. A prudent course of action entails the recommendation that the CDA institute rigorous monitoring and regulatory mechanisms to curb unauthorized land usage following the master plan's revision. These systems should encompass contemporary methodologies, a robust public awareness campaign, and stringent enforcement of relevant legal provisions, ensuring responsible and sustainable land utilization practices within the city.

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AUTHOR CONTRIBUTIONS

Conceptualization: I.A. and M.W.; methodology: I.A., S.H., and M.W.; software, I.A., M.K.L., and M.W; validation, I.A., S.H., and M.W.; formal analysis: M.W., S.H., and I.A.; investigation: I.A.; data curation: I.A., S.H., and M.W.; writing original draft: I.A.; writing – review and editing: M.W., I.A., and M.K.L.; visualization: M.W. and M.K.L. All authors have read and agreed to the submitted version of the manuscript.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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