Environmental Impact Assessment Review 105 (2024) 107396

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

journal homepage: www.elsevier.com/locate/eiar

Urbanization-led land cover change impacts terrestrial carbon storage capacity: A high-resolution remote sensing-based nation-wide assessment in Pakistan (1990–2020)

Mirza Waleed [a], Muhammad Sajjad [a,b,*], Muhammad Shareef Shazil [c]

[a] Department of Geography, Hong Kong Baptist University, Hong Kong Special Administrative Region
[b] Centre for Geo-computational Studies, Hong Kong Baptist University, Hong Kong Special Administrative Region
[c] Department of Space Science, University of Punjab, Pakistan

ARTICLE INFO

Keywords:
LULC
Google earth engine
Cloud computing
Carbon storage change detection
Climate mitigation

ABSTRACT

While carbon sequestration is significant to achieve the *net zero* and plays an important role in climate change mitigation, urbanization-led land use land cover (LULC) changes are causing significant impacts on the carbon stocks of terrestrial ecosystems. Despite rapid urbanization in Pakistan, previous studies focus solely on localized areas without documenting the influence of urbanization on carbon stock. Hence, insights regarding the carbon storage dynamics (CSD) in response to LULC changes become essential to drive informed decisions and policies. In this context, we leverage high-resolution (30 m) remote sensing data to evaluate and map the grid-level spatial-temporal interactions between urbanization and CSD at the national scale in Pakistan during 1990–2020. To do so, multi-sensor earth observation data are retrieved and processed using the Google Earth Engine and the Integrated Valuation of Ecosystem Services and Tradeoffs models. Our findings indicate that urban areas have expanded exponentially (an increase of ~1040%), resulting in reduced carbon storage (a decrease of $\sim -5\%$). Major cities (e.g., Karachi, Lahore, Faisalabad) showed less urban sprawl while emerging cities (e.g., Rawalpindi and Peshawar) demonstrated higher urban sprawl, primarily due to shifting patterns from rangeland (~47%) and agriculture (~35%) to built-up class. Though some afforestation projects have increased forest carbon stocks in the northern region, there is a large north-south spatial heterogeneity in carbon storage loss across Pakistan. The presented high-resolution mapping of CSD over the past three decades advances our understanding of where and how much urbanization has influenced carbon sequestration, nationally. Considering the results, this study emphasizes the need for policies and management approaches that support sustainable urbanization, which does not compromise carbon pools in the country.

1. Introduction

Carbon storage dynamics (CSD) play an essential role in the mitigation of the effects of climate change, and land use land cover (LULC) changes are among the key factors that impact carbon storage in terrestrial ecosystems. In a world where climate change poses a significant threat, understanding CSD in response to LULC changes is crucial to design and developing sustainable land management practices and policies. Urbanization as a major contributor to LULC changes is a global issue, leading to severe consequences, including overpopulation, food security, air and water pollution, global warming, and climate change (Kuddus et al., 2020). Due to the lack of maintained urban infrastructure and poor land use policies in urban areas, developing countries are comparatively more affected than developed nations (Waleed et al., 2023a). For instance, in 2019, the United Nations estimated that 4.2 billion people (making up almost half of the world's total population) live in urban areas, and the number is predicted to cross 6 billion by 2041 (Gu et al., 2021). Under the ongoing climate changes, rapid urbanization poses serious challenges including complex land use issues, reduction in vegetation cover, and deforestation (Chen et al., 2021; Song et al., 2020).

On a larger scale, urbanization-led LULC changes, especially the conversion of natural ecosystems to built-up areas, influence carbon stocks by compromising the carbon storage capacity of regions (Kuddus

* Corresponding author at: Office AAB-1222, Department of Geography, Academic and Administration Building, Hong Kong Baptist University, Kowloon Tong, Hong Kong Special Administrative Region.
E-mail address: mah.sajjad@hotmail.com (M. Sajjad).

https://doi.org/10.1016/j.eiar.2023.107396
Received 4 July 2023; Received in revised form 9 December 2023; Accepted 11 December 2023

et al., 2020). This reduction has multi-scale implications for global warming and climate change. Reduced carbon storage in response to LULC changes results in increased atmospheric CO_2 concentrations, which can lead to a larger greenhouse effect—ultimately influencing climate change regulation at various scales (i.e., national, regional, and global) (Fahad et al., 2021; Zhu et al., 2022). However, the influence of LULC change on CSD is a complex issue that prerequisites in-depth research and assessment. To provide references for localized decisions and resource allocation in the context of land resource management and maintaining carbon stocks, such assessments need to be carried out at finer spatial resolutions (Chuai et al., 2022; Fan et al., 2022).

Remote sensing techniques and data have revolutionized our ability to monitor and manage the Earth's natural resources and ecosystem services. With the advent of satellite-based remote sensing, it is now possible to obtain spatially explicit and timely information on LULC changes. These assessments pave the ways to develop integrated methodologies and evaluate the impact of LULC on various ecosystem services including carbon stock (Toru and Kibret, 2019; Waleed and Sajjad, 2022a). Such assessments provide crucial references to track urbanization-induced changes in LULC and how it results in reduced carbon storage due to the degradation of natural ecosystems (Luisetti et al., 2019; Rimal et al., 2019). Remote sensing-based evaluation of carbon stock in various ecosystems, including forests, grasslands, and wetlands, allows us to understand the carbon balance and potential sources and sinks of greenhouse gases, which are crucial for mitigating climate change (Canedoli et al., 2020; Zhang et al., 2015). However, supporting national policies requires nationwide comprehensive assessments, but with the amount of a petabyte of satellite data required for such evaluations, computational capabilities are becoming a bottleneck due to large processing requirements.

Google Earth Engine (GEE) is a cloud computing tool widely used for large-scale geospatial analysis. The free-to-use GEE platform provided by Google can process petabytes of data within seconds (Mutanga and Kumar, 2019). Furthermore, it gives access to a vast data catalog, including decades of multi-sensor earth observation archives, enabling well-organized time series analysis across a large geographical area (Amani et al., 2020). Its flexible programming interface allows users to employ pre-defined algorithms or create their own using JavaScript or Python (Waleed and Sajjad, 2022b). Additionally, GEE provides preloaded Machine Learning (ML) models that users can apply to their spatial data for various purposes, such as LULC-supervised classification (Avci et al., 2023). Recently, Random Forest (RF) has emerged as a robust, efficient, and highly accurate ML algorithm for mapping LULC in heterogenous landscapes (Waleed and Sajjad, 2022a). Carbon stock estimation is conventionally evaluated using various computer models, among which the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST®: https://naturalcapitalproject.stanford.edu/software/invest) carbon model has gained popularity in recent years (He et al., 2016; Li et al., 2022; Piyathilake et al., 2022; Wang et al., 2022). The InVEST model uses land cover data and optional biophysical and economic factors to assess carbon stocks in various land use classes. As a key output, the model helps identify different areas with high carbon storage potential and quantify the impact of LULC changes on CSD. Furthermore, the outputs are used to map the spatial inconsistencies and patterns in CSD to pinpoint the priority intervention areas.

Pakistan—a nation of ~230 million people—faces several environmental challenges, making it the fifth most vulnerable country due to climate change and associated threats (Ullah et al., 2022). Recent studies reported a higher urbanization rate in Pakistan than in other South Asian countries (Abdullah et al., 2019; Waleed and Sajjad, 2022a), which creates several sustainable development-related challenges for the country. While the country's contribution to global carbon emissions is very low, its emissions have experienced a significant increase in the recent two decades. Under this situation, the lack of comprehensive research on urbanization and carbon stock, especially at a national scale, is a major hindrance to formulating informed policies regarding sustainable land management practices as well as carbon storage monitoring. Hence, high-resolution mapping of CSD in response to LULC change could progressively inform policies, resulting in the sustainable development of the country. In this context, an important question is that what are the possible opportunities to leverage open high-resolution datasets to investigate long-term mapping of carbon storage change. Similarly, other important questions are "how land use and land cover change are influencing the carbon storage capacity at national scales?" and "are there any geographical disparities in LULC-induced change in carbon storage that can be identified via high-resolution remote-sensing data. The availability of global high-resolution datasets and cloud computing-based GEE platform opens doors to exciting possibilities, (i.e., high resolution mapping of land cover at national level and its influence on carbon storage), which can progressively assist in answering these questions. Therefore, the present study leverages cloud computational capabilities and open access satellite dataset, spectral indices, and InVEST carbon model to assess and map LULC patterns and their impact on CSD in Pakistan during the past three decades (1990–2020). While the results of this study will provide valuable insights regarding the impacts of LULC change on carbon stocks, the high-resolution mapping (30 m spatial resolution) will help devise targeted strategies for carbon sink preservation through sustainable land use practices. Also, the findings and produced fine-scale mapping along with the development of the first high-resolution nationally consistent LULC and CSD database could be used for further evaluations in this research domain and beyond—acting as a baseline.

2. Methodology

2.1. Study area

Developing countries lack assessment of CSD due to limited financial resources, technological capacity, and institutional expertise. Among developing countries, Pakistan (Fig. 1a) surpasses others, due to its special geographical location, rising population, climate change effects, and disaster vulnerability levels (Akhtar et al., 2023; Sajjad et al., 2023). In Pakistan, the energy sector (60%), agriculture (20%), and industry (20%) are the primary emission sources of GHGs, with the energy sector being the highest due to the country's reliance on non-sustainable energy sources including coal, oil, and gas primarily for power generation (UNFCCC, G, 2021). On the contrary, the agriculture and industry sectors are the second and third largest sources of GHGs emissions due to the extensive use of fertilizers and transportation respectively. Pakistan has experienced a steady increase in carbon emissions, primarily driven by its dependence on fossil fuels in energy production and transportation (shown in Fig. 1b, and d). While carbon emissions are inevitable, they are being balanced with different ecosystem services available in the country. For instance, Pakistan possesses the potential to function as a carbon sink through its expansive forests and ecosystems capable of sequestering carbon dioxide. However, deforestation, climate change, and other factors pose threats to Pakistan's carbon sinks, as the rapid clearance of forests releases carbon dioxide into the atmosphere, diminishing the country's capacity for carbon absorption (Mannan et al., 2018). Therefore, comprehensive national-scale studies focusing on historical and current carbon storage status are needed to provide a baseline understanding of the carbon sequestration potential and trends, enabling effective climate change mitigation strategies and informed decision-making on sustainable land management practices.

While CSD assessment studies at a national scale are crucial as they provide a holistic and comprehensive understanding of a country's carbon emissions, they often require much higher computational power (Zhu et al., 2022). Pakistan has an area of 796,095 km^2, which creates hurdles for national scale analysis due to large processing requirements. To counter this, a recent study by Naboureh et al. (2023) proposed dividing the study area into strata zones based on the Köppen Geiger climate classification system. Following that, the area of Pakistan was

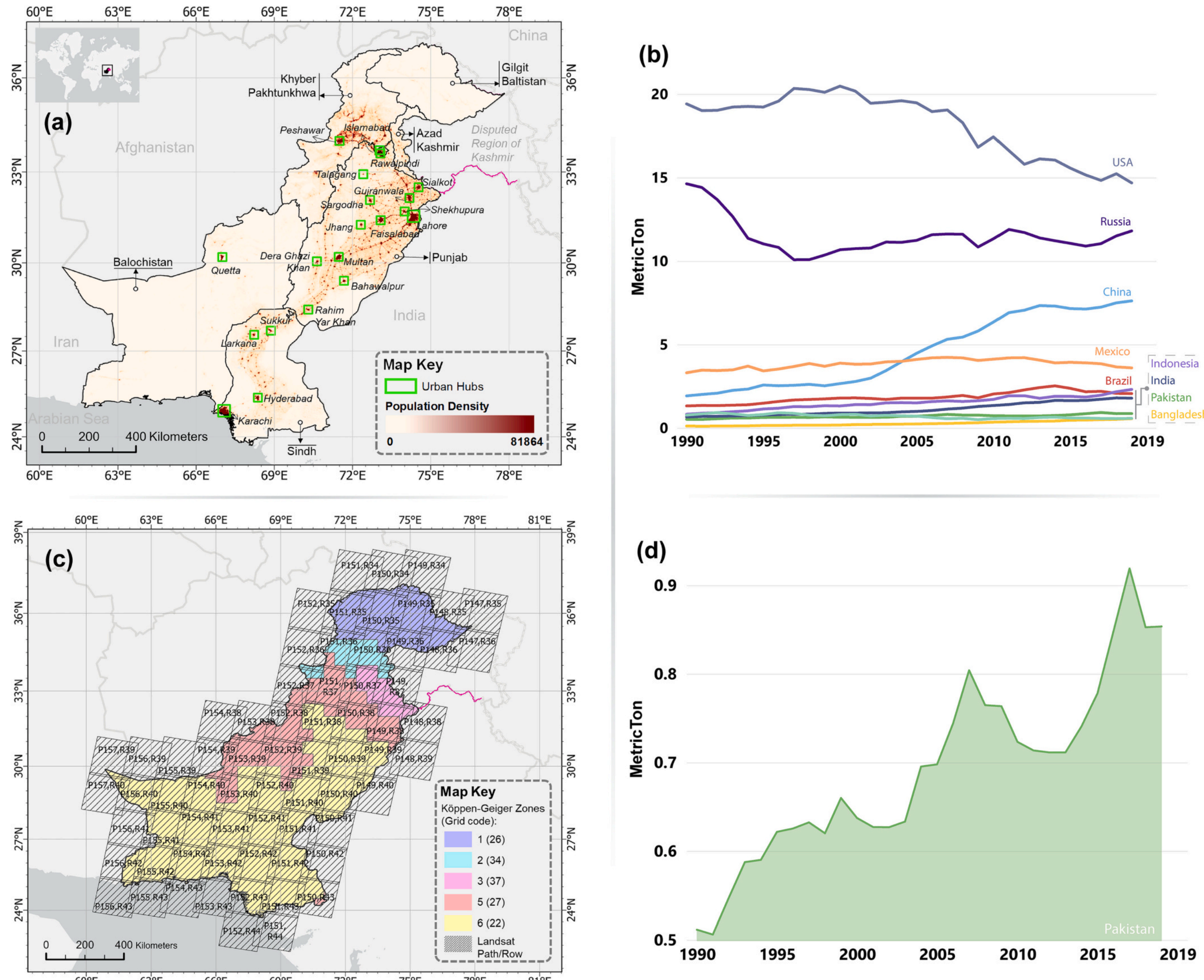

Fig. 1. (a) Study Area map of Pakistan with population density. The green box highlights the top 20 population-wise cities in Pakistan. (b) Carbon emissions per capita, for the top 9 countries between 1990 and 2019. (c) Location of sub-zones based on Koppen-Geiger climate classification system, and Landsat path row coverage. Note, Koppen-Geiger-based grid codes are given in brackets, whereas numbers 1–6 represent simplified labels for each zone. Furthermore, the "P" and "R" in labels represent the Path and Row of Landsat images, respectively. Lastly (d) Carbon emissions per capita for Pakistan between 1990 and 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

divided into six zones shown in Fig. 1c. The Köppen system divides the areas based on vegetation, temperature, and precipitation patterns, resulting in homogenous area zones (Peel et al., 2007).

2.2. Data acquisition and preparation

The study is conducted in several steps including data acquisition and preprocessing, collecting reference data, machine learning modelling, post-processing, high-resolution LULC mapping, LULC change detection and transitions, and the influence of LULC changes on carbon storage during 1990–2020. In the first stage of data acquisition and preprocessing we filtered Landsat-5 Thematic Mapper (TM) tier-1 Surface Reflectance (SR) and Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) tier-1 SR data from the GEE data catalogues in the form of an image collection. As LULC change is a slow process (Waleed and Sajjad, 2022a), we divided our analysis into four distinct periods, specifically 1990, 2000, 2010, and 2020. To obtain the necessary data for our study, we used multi-source data including Landsat-5 TM tier-1 SR data for 1990, 2000, and 2010, and Landsat-8 OLI tier-1 SR data for 2020. We avoided using Landsat-7 data for 2000 and 2010 due to scan-line errors after 2003 (Scaramuzza and Barsi, 2005). In addition to the satellite observation-based data, we utilized vector data for provincial and district-level boundaries and population density. Detailed information regarding the data used in the study, including their acquisition dates and sources, is given in Table 1.

2.2.1. Preprocessing

After data acquisition, data processing was performed which includes atmospheric corrections, filtering images based on time intervals, and taking the best pixels using mean. Atmospheric correction minimizes atmospheric disturbances such as haze and cloud cover (Chavez, 1988). The haze effect is removed by identifying the darkest pixel value in each band and subtracting that value from each pixel. For cloud removal, the *QA_PIXEL* band of Landsat (5 and 8) was used to mask any pixel identified as a cloud (Shafi et al., 2023). To generate the year 1990 mosaic, we used Landsat-5 images from 1989 to 1991 with cloud coverage of <30%. For the year 2000, and 2010 mosaic, we filter images between 1999 and 2001 and 2009 to 2011 respectively, both with <30%

Table 1
Details of Datasets used in this study and their sources.

Name of dataset	Resolution	Acquisition date	Source
FABDEM (Forest and Buildings removed Copernicus DEM)	30 m	2022	https://data.bris.ac.uk/data/dataset/25wfy0f9ukoge2gs7a5mqpq2j7
Landsat-5	30 m	Jan-Aug (1990, 2000, 2010)	https://developers.google.com/earth-engine/datasets/catalog/landsat-5
Landsat-8	30 m	Jan-Aug (2020)	https://developers.google.com/earth-engine/datasets/catalog/landsat-8
Administrative Boundaries of Pakistan – Vector Data		2022	https://data.humdata.org/dataset/cod-ab-pak
Köppen-Geiger Climate Classification – Vector Data		2020	https://datacatalog.worldbank.org/search/dataset/0042325
MCD12Q1.061 MODIS Land Cover Type Yearly Global	500 m	2000,2010,2020	https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MCD12Q1
Tsinghua FROM-GLC Year of Change to Impervious Surface	30 m	1990–2020	https://developers.google.com/earth-engine/datasets/catalog/Tsinghua_FROM-GLC_GAIA_v10
JRC Global Surface Water Mapping Layers, v1.4	30 m	1990–2020	https://developers.google.com/earth-engine/datasets/catalog/JRC_GSW1_4_GlobalSurfaceWater
Global Forest Cover Change (GFCC) Tree Cover	30 m	2000,2010	https://developers.google.com/earth-engine/datasets/catalog/NASA_MEASURES_GFCC_TC_v3
GlobCover: Global Land Cover Map	300 m	2009	https://developers.google.com/earth-engine/datasets/catalog/ESA_GLOBCOVER_L4_200901_200912_V2_3

cloud coverage threshold. Lastly, for the 2020 mosaic, we filter images from the Landsat-8 image collection between 2019 and 2021. For all four mosaics, we filter images with <30% cloud coverage, and then in the end, we took mean values for each mosaic to ensure the best pixel representation of time series data (Shafizadeh-Moghadam et al., 2021). Combining these images using the mean pixel approach can create a more complete and accurate representation of the features in different zones for a particular year (Waleed and Sajjad, 2022a). This approach also reduces the impact of missing data and cloud interference, which can be significant sources of error in change detection analysis. The overall methodology adopted in this study is illustrated in Fig. 2.

2.2.2. *Feature extraction*

Spectral Indices (SIs) change the conventional multi-spectral data into a single image which depicts the enhanced characteristics of a phenomenon (Bijeesh and Narasimhamurthy, 2019). They are well known because of their noise reduction and feature enhancement capabilities (Xue and Su, 2017). From the literature, the five most common SIs were taken which include the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Enhanced Vegetation Index (EVI), and Modified Normalized Difference Water Index (MNDWI). Details of these SIs including their equation and reference are provided in Table 2.

2.2.3. *Reference data and training*

For model training and testing data, this study used various data sources as a reference, including Google Earth images, MCD12Q1.061 MODIS Land Cover Type Yearly Global, Tsinghua FROM-GLC Year of Change to Impervious Surface, JRC Global Surface Water Mapping Layers, v1.4, Global Forest Cover Change (GFCC) Tree Cover, and GlobCover: Global Land Cover Map product. Details and sources of these datasets are provided in Table 1. Along with these datasets, SIs were also used to create samples. For sampling, we used a random stratified sampling approach to collect approximately 10,000 point samples each year (Waleed and Sajjad, 2022a). After creating these samples, they were then divided into a 70/30 ratio for training and validation respectively.

2.3. *Machine learning-based modelling and post-processing*

Once our training and validation data were finalized, we divided the total classification workload of national scale LULC classification into 6 zones, each zone having an individual RF-based classifier. Each RF model was supplied with input imagery along with features including SIs, and Digital Elevation Model (DEM). The end output of each model was then mosaicked, creating the national scale LULC product for each respective year.

Subsequently, post-processing is carried out, which is a crucial step in finalizing end-classification products that involve LULC majority filtering, accuracy assessment, and change detection. The majority filter, or the 3×3 mode filter is used to improve image classification accuracy by removing isolated pixels (Stuckens et al., 2000). It investigates the values of a small neighbourhood of pixels within the image and then replaces the center pixel value with the most frequently occurring value in the neighbourhood (Hütt et al., 2020). This helps to remove isolated pixels that do not belong to any class and smooth out the image by removing small inconsistencies in the classification. This filtering technique was applied to remove unwanted noise and improve the accuracy of the classification before the accuracy assessment. For accuracy assessment, precision, recall, and F1-Score (F1s) matrices were used to evaluate the end performance of the classification product (Waleed and Sajjad, 2022a). These matrices help to assess the accuracy of the classifier by determining True Positive (TP) rate, True Negative (TN) rate, False Positive (FP) rate, and False Negative (FN) rate (Zhou and Jing, 2022). The terms precision and recall are often used to define the end accuracy metric. Precision is the ratio of correctly classified instances (TP) and the total instances that the model classifies (TP+ FP) and is given as Eq. (1).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

The recall is the ratio of correctly classified instances (TP) and the total positive instances present in the data (TP+ FP). The model can correctly detect positive instances and is given as Eq. (2).

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

F1s is the measure of the overall performance of the model. It considers both precision and recall and is given by Eq. (3).

$$F1s = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{3}$$

Other than these accuracy assessment techniques, a confusion matrix is also generated to compare the predicted class labels with the true class labels. A confusion matrix is a table that shows the number of true classified pixels in a diagonal, along with false classified pixels corresponding to each row and column (Waleed et al., 2023b).

In LULC studies, the last post-processing step is “change detection”. Change detection analysis involves the comparison of two or more images at different temporal intervals. Conventionally, change detection

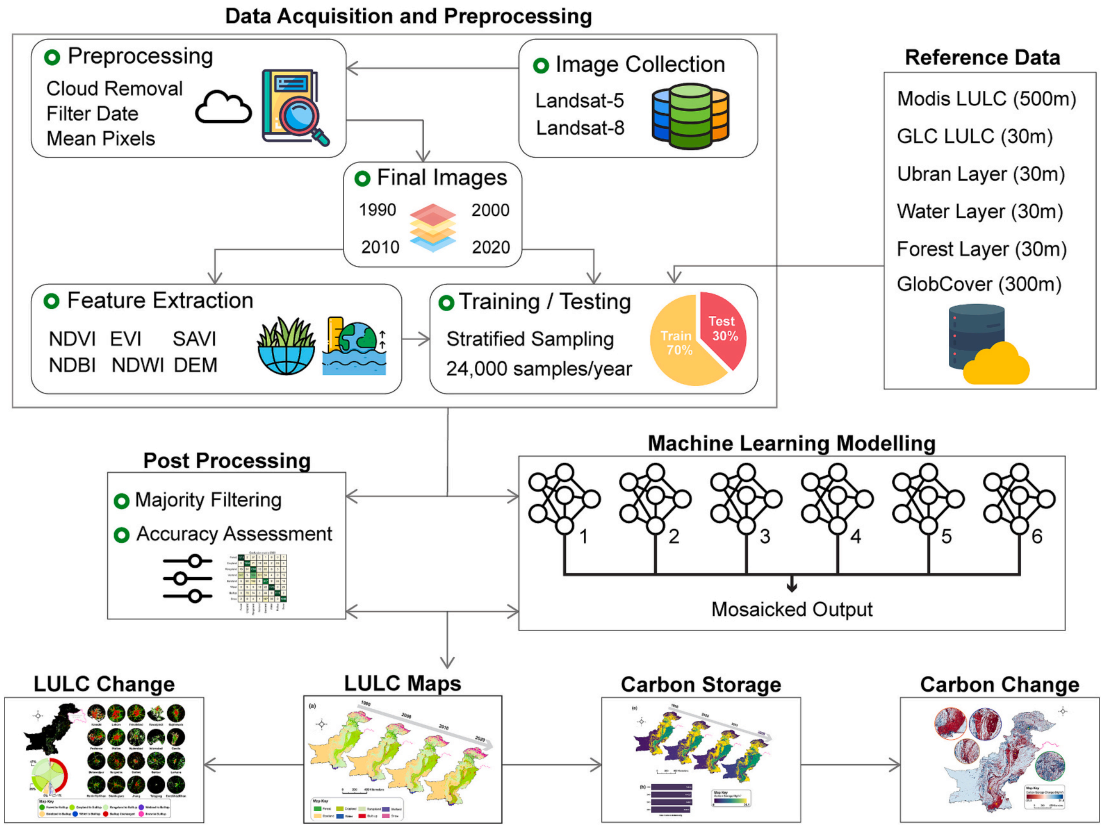

Fig. 2. Methodology flowchart.

Table 2
Details of spectral indices used in this study.

Name	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - RED}{NIR + RED}$	(Liu and Huete, 1995)
Normalized Difference Built-up Index (NDBI)	$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$	(Zha et al., 2003)
Enhanced Vegetation Index (EVI)	$EVI = 2.5 \times \frac{NIR - RED}{NIR + R} + 1$	(Huete et al., 2002)
Modified Normalized Difference Water Index (mNDWI)	$MNDWI = \frac{GREEN - SWIR}{GREEN + SWIR}$	(Xu, 2006)

for two image instances is performed by subtracting the initial image from the final image (Gong et al., 2022). Change detection also involves change transition analysis, which analyzes the flow of change of each class in LULC from the initial to the final class over a period (Waleed et al., 2023b). In this study, change detection analysis was performed using the "*change detection wizard*" function of ArcGIS Pro V3 software (available at: https://www.esri.com/en-us/arcgis/products/arcgis-pro).

2.4. *Carbon storage and its dynamics in response to LULC transitions*

In this study, we utilized the carbon storage and sequestration model from the InVEST software suite developed by the Natural Capital Project (available at: www.naturalcapitalproject.stanford.edu/software/invest/invest-dowloads-data) to assess the total carbon stocks of Pakistan. This model is a widely used open-source tool due to its simplicity and efficiency. As the model follows the carbon cycle, it provides an inclusive estimate of the total carbon stock in the study area by considering four carbon pools: Above-ground Carbon (Ca), Below-ground Biomass (Cb), Dead Organic Matter (Cd), and Soil Carbon (Cs). The total carbon storage is then calculated by aggregating the carbon density of all LULC types. The specific equations used to quantify carbons storage, and carbon storage per pixel of each LULC type are provided as Eqs. (4) and (5) respectively (Kafy et al., 2023; Zhu et al., 2022). To use the InVEST carbon model, two initial data inputs are required: LULC data and carbon density (carbon pools) data of each LULC type. Due to the unavailability of field carbon pool data on a national scale in Pakistan, we relied on the literature and acquired the values of different carbon pools previously reported in peer-reviewed studies. *Ca* pool data were obtained from the Intergovernmental Pannel on Climate Change (IPCC) 2006 report (IPCC, 2006), whereas *Cb* storage values of the LULC types containing woody biomass were estimated using the "root to shoot" ratio method (Liang et al., 2021; Piyathilake et al., 2022). The details of other carbon pools and their source information are provided in Table 3.

$$Carbon\ Storage = Ca + Cb + Cd + Cs \tag{4}$$

$$Carbon\ Storage\ (pixel) = \sum_{i=1}^{n} A_k \times (Ca + Cb + Cd + CS), (k = 1, 2, \dots, n) \tag{5}$$

where A_k is the area of the respective land use class.

3. Results

3.1. *Satellite-derived LULC dynamics*

Ensuring the reliability and accuracy of land use and land cover (LULC) classification is crucial to identify errors and uncertainties in the mapping process and supports the improvement of future maps (Abdullah et al., 2019). The results of the accuracy assessment are shown in Fig. 3. It is evident that accuracy assessment shows good

Table 3
Carbon pools used to estimate carbon storage in different land use land covers in Pakistan.

Class	Ca (Mg/Ha)	Cb (Mg/Ha)	Cs (Mg/Ha)	Cd (Mg/Ha)	Justification
Forest	54	115	172.5	4.9	(Liang et al., 2021; Piyathilake et al., 2022)
Rangeland	35	86.9	111	3.2	(He et al., 2016; Liang et al., 2021; Zhao et al., 2019)
Built up	3	0	23.3	2.94	(Liang et al., 2021; Piyathilake et al., 2022)
Water Body	1.6	0	119	0	(Liang et al., 2021)
Cropland	11.9	99	66	1	(He et al., 2016; Liang et al., 2021; Zhao et al., 2019)
Bareland	0.63	4.95	111	0	(He et al., 2016; Zhao et al., 2019)
Wetlands	0	0	298	0	(Piyathilake et al., 2022; Zhao et al., 2019)

agreement of classification results with F1s results above 0.80 for all classes except rangeland and wetlands. For these two classes, the mean F1s score is above 0.7 for rangeland, and 0.55 for wetlands, which shows their validity. In the case of wetlands, due to the unavailability of reference sample points the F1-score is quite low (~0.4) for 1990, 2000, and 2020 indicating it should be avoided for certain applications. However other classes showed reliable output. For recall and precision, scores follow a similar trend as of F1-score with the highest accurate classes being built-up, bare land, water, snow, cropland, and forest, and the least accurate being rangeland and wetlands. Similarly, the confusion matrix (Fig. 3b) shows good agreement between actual and predicted, where rows are actual, and columns are predicted classes.

Fig. 4a shows the LULC maps for 1990, 2000, 2010, and 2020 whereas Fig. 4b shows the ribbon chart depicting the percentage share of each LULC, class each year. The maps of the LULC classification consist of eight classes including built-up, forest, water, wetlands, rangeland, cropland, snow, and bare land. Overall, the LULC classification results show consistent landscape patterns, with the majority of cropland located in Punjab and Sindh province, and most of the forest cover located in northern areas each year. The forest cover saw a significant increase in its area from 1990 to 2000 but experienced a sharp decline of 36% by 2010. However, by 2020, it again experienced a rise of 83%. Area-wise, between 1990 and 2020 forest class showed an increase in area from ~18,589 Km^2 in 1990 to ~23,528 Km^2 in 2020. The details of the area of each LULC class per year in Km^2, area percentage distribution per year, and area change transition are provided in the supplementary file as Table S1, S2, and S3, respectively.

The cropland area remained relatively stable, with only a 29% increase from 1990 to 2020 (from 210,903 Km^2 in 1990 to 271,958 Km^2 in 2020. Rangeland showed an unstable trend over the four decades, with a slight increase from 1990 to 2000, a decrease by 2010, and a further reduction by 2020, resulting in an overall decline of 31% in its area. Wetlands also showed an unstable trend with a slight increase in the first decade (1990 to 2000), followed by a decrease by 2010. However, by 2020, there was a significant increase of 147%. Bare land also showed a similar pattern, with a slight increase from 1990 to 2000, a decrease by 2010, and another slight increase by 2020. The water area remained relatively stable, with only a slight increase of 37% from 1990 to 2020. Among all, the built-up has been the most active class, with a significant increase of 1040% from 1990 to 2020, showing the rapid urbanization phenomenon in Pakistan. Specifically, the area of built-up class increased from 3314 Km^2 in 1990 to 37,786 Km^2 in 2020, showing a tremendous increase. Snow cover also fluctuated, with a slight increase from 1990 to 2000, followed by a decrease by 2010, and then a significant increase of 35% by 2020. Notably, two classes, cropland, and bare land, remained relatively stable throughout the four decades. Area-wise, Fig. 4b shows the percent share of each land-use class each year. From Fig. 4b, it is observed that the built-up percent increased rapidly since 2000; indicating that the era can be regarded as the highest urbanization period. The share percentage of cropland and rangeland classes increased and decreased respectively in the last decade, while forest, wetlands, bareland, water, and snow classes showed fluctuations in their share percentage. Notably, the percentage share of cropland increased from 18% in 2010 to 23% in 2020, whereas the percentage share of rangeland decreased from 33% in 2010 to 22% in 2020.

3.2. LULC transitions over the past three decades (1990–2020)

The land use classification analysis of Pakistan for four different periods (1990, 2000, 2010, and 2020) revealed significant changes in land use patterns. The change transition analysis shown in Fig. 5, provided insights into the conversion of land use classes over time, indicating trends such as urbanization, deforestation, and agricultural expansion. The inset maps of the top 20 cities provided a more detailed picture of the land use changes in these areas, highlighting the intensity and spatial distribution of the changes. The results indicate that urban areas have expanded significantly over time, at the expense of rangeland and cropland areas, particularly in and around the top 20 cities. For instance, in the mega-cities, such as Karachi, Lahore, and Faisalabad, much of the conversion is from cropland to urban. In Rawalpindi, most of the conversion is from rangeland and cropland to built-up. Cities including Multan and Hyderabad show the highest spatial extent of urban expansion at the expense of cropland. Lastly, Fig. 5 also shows the Sankey diagram, which highlights the conversion of different land use classes into built-up. From this, it is observed that the largest conversion was from rangeland to urban, which accounts for a total of 47% between 1990 and 2020. Similarly, cropland and barren class showed conversion of 35% and 9% between the last 30 years, respectively.

3.3. Mapping built-up area influx (urban sprawl) between 1990 and 2020

The initial LULC classification maps (Fig. 4) indicate that the area of built-up class rapidly increases which suggests that there might be many cities undergoing high urbanization. To counter this, an urban sprawl map is prepared and is depicted in Fig. 6. Similar to Fig. 5, Fig. 6 also shows inset maps of the top 20 population-wise cities and visualizes their urban growth. The Figure comprises two parts; Fig. 6a with the inset maps, while Fig. 6b represents the share percentage of different land use classes. From inset maps (Fig. 6a), it is evident that the major urbanization occurred in the 1990–2000 period, followed by the development in the 2010–2020 period. The mega-cities, including Karachi, Lahore, and Faisalabad, showed comparatively lower urban sprawl than other cities, such as Peshawar, Multan, and Hyderabad. Among all the top 20 cities, higher spatial patterns of urban sprawl are observed for Rawalpindi, Peshawar, Hyderabad, and Quetta. Furthermore, in terms of recent urbanization, Rawalpindi and Islamabad showed the highest spatial patterns in the recent 2010–2020 period.

3.4. High-resolution grid-level total carbon storage mapping

Fig. 7a shows carbon storage maps for four different periods (1990, 2000, 2010, and 2020) at the national scale, generated using the InVEST model. The maps reveal significant changes in carbon storage over the 30 years, with some areas experiencing increases in carbon storage while others experiencing decreases. The results suggest that carbon storage has decreased in areas of intensive land use change, such as urbanization and agricultural expansion, while some forested areas have shown increases in carbon storage. Specifically, the urban hotspot regions, such as the previous top 20 cities, showed the least carbon storage. Comparatively, northern areas of Pakistan (having a large

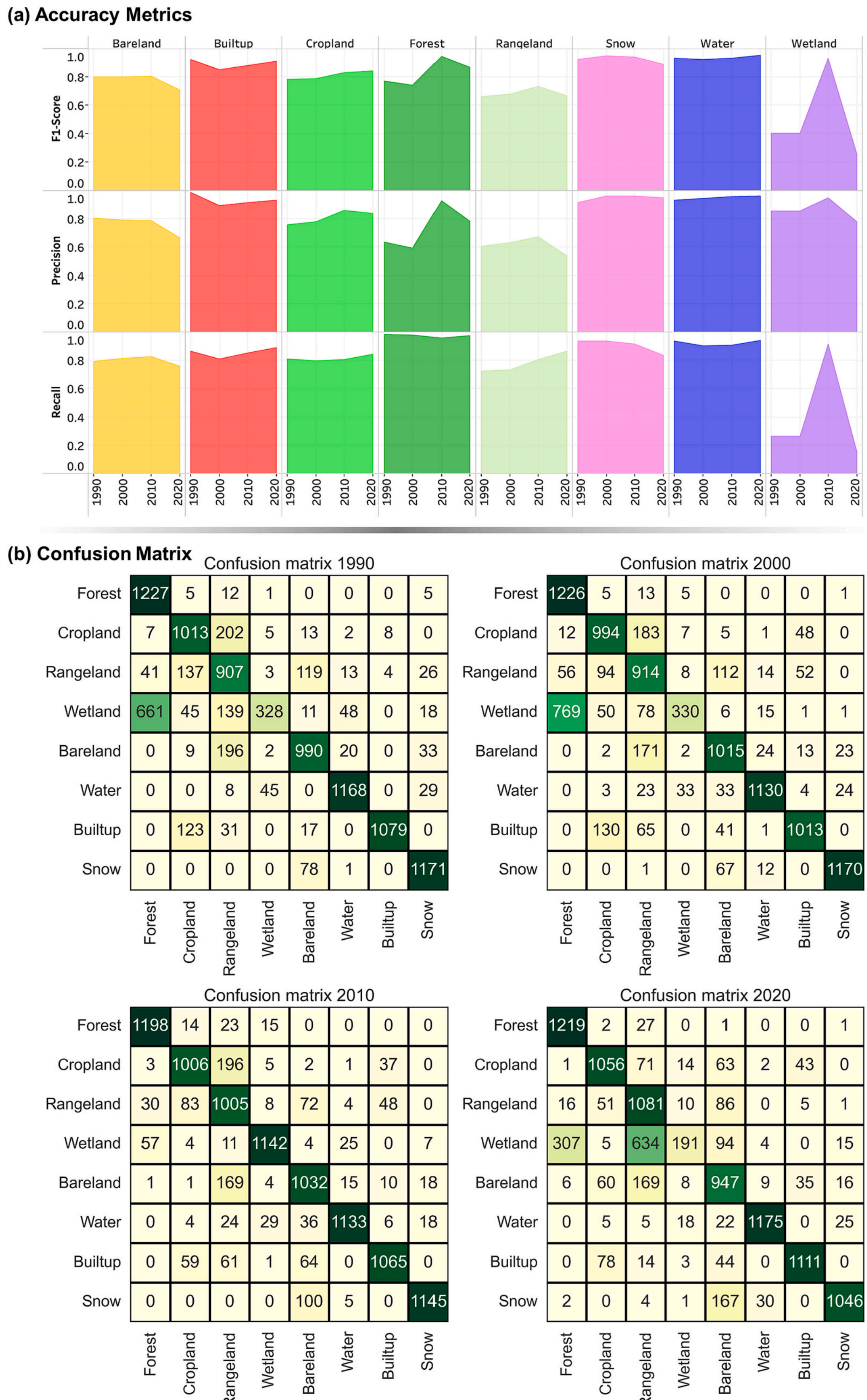

Fig. 3. (a) Accuracy assessment metrics (F1-score, Precision, and Recall) for each land use land cover class and each year, and (b) Confusion matrix for each year classification.

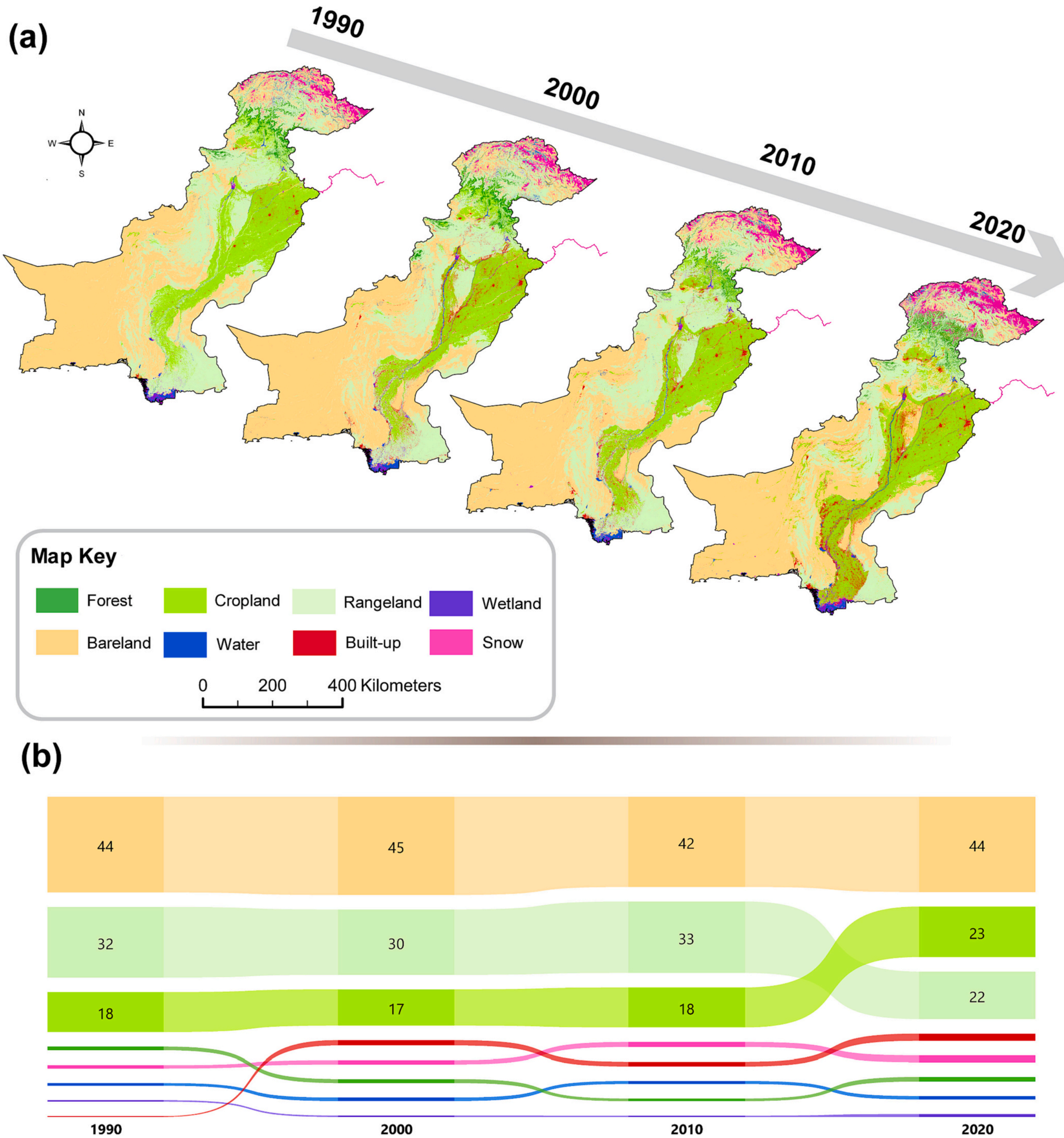

Fig. 4. (a) Land use land cover (LULC) classified maps, and (b) LULC percent area (%) per class. Note that the colors in the ribbon chart in (b) are in line with the map key of LULC maps. For detailed statistics used in Fig. 4b, see Table S2.

proportion of forest class) showed the highest volume of carbon storage, whereas the Thal desert and region of Balochistan province showed the least carbon storage. The multi-temporal maps also highlight the decreasing trends of carbon storage in the region, where initially in 1990 the southern region (Sindh) and northern region (Khyber Pakhtunkhwa and upper Punjab) showed higher carbon storage than the upcoming years. The decreasing trend is prominent in regions undergoing either deforestation (northern areas) or agricultural extension (southern areas). Furthermore, Fig. 7b shows the total carbon storage value in Pakistan each year, in which the carbon storage decreased from 19,464 Mg/m^2 in 1990 to 18,452 Mg/m^2 in 2020 (~5% overall reduction).

Fig. 8 shows the change in carbon storage in Pakistan from 1990 to 2020, highlighting the spatial distribution and magnitude of carbon loss and gain over time. The inset maps in Fig. 8 visualize key regions where there has been a considerable increase or decrease in the last three decades. Overall, Fig. 8 indicates that there has been a significant decrease in carbon storage in some regions of Pakistan, particularly in the northwest and southeast parts, due to deforestation and agricultural extension, respectively. However, some areas in the northern part of the country show an increase in carbon storage, possibly due to reforestation and afforestation efforts. The map and its results provide valuable information for policymakers and stakeholders to better understand the

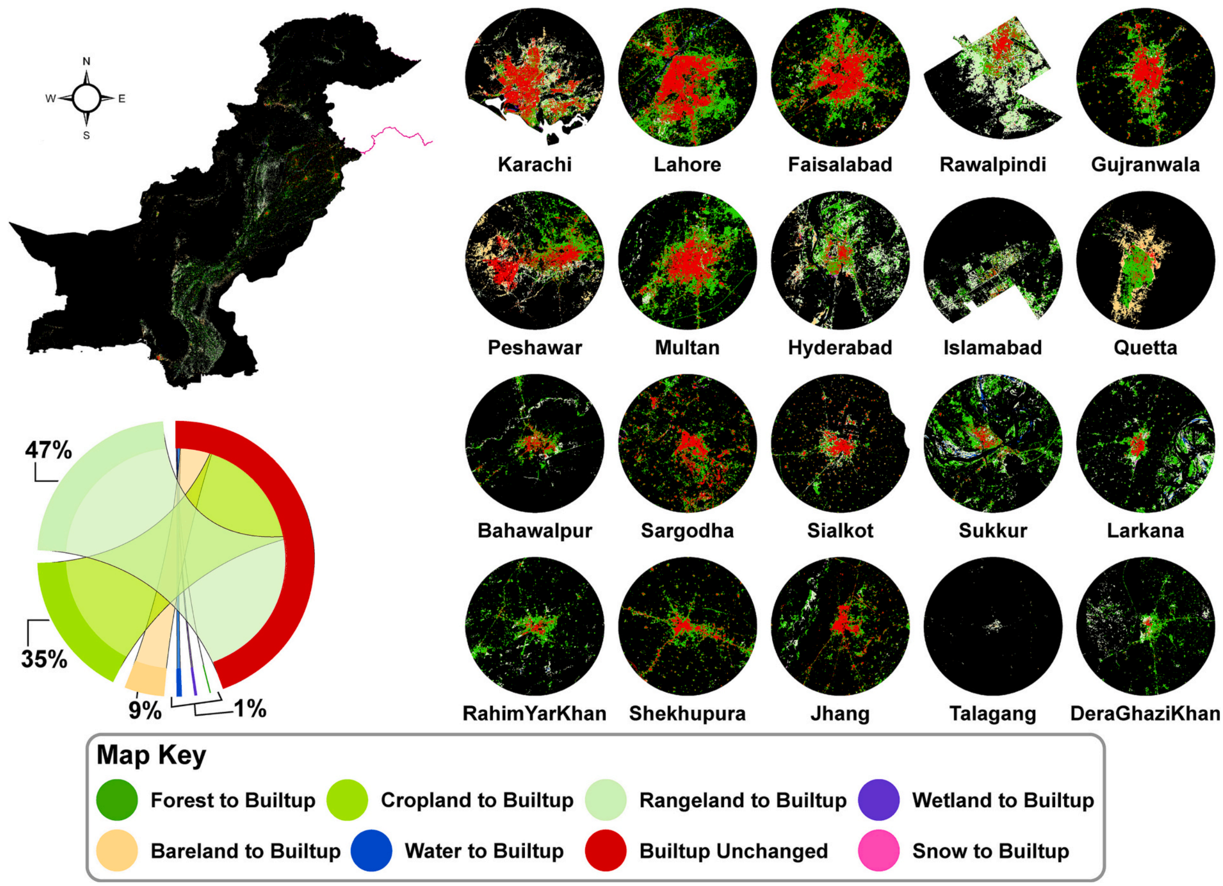

Fig. 5. Change Transition map showing top 20 cities inset maps (sorted based on population) and cord diagram showing the transition percentage change of different classes into urban for Pakistan between 1990 and 2020.

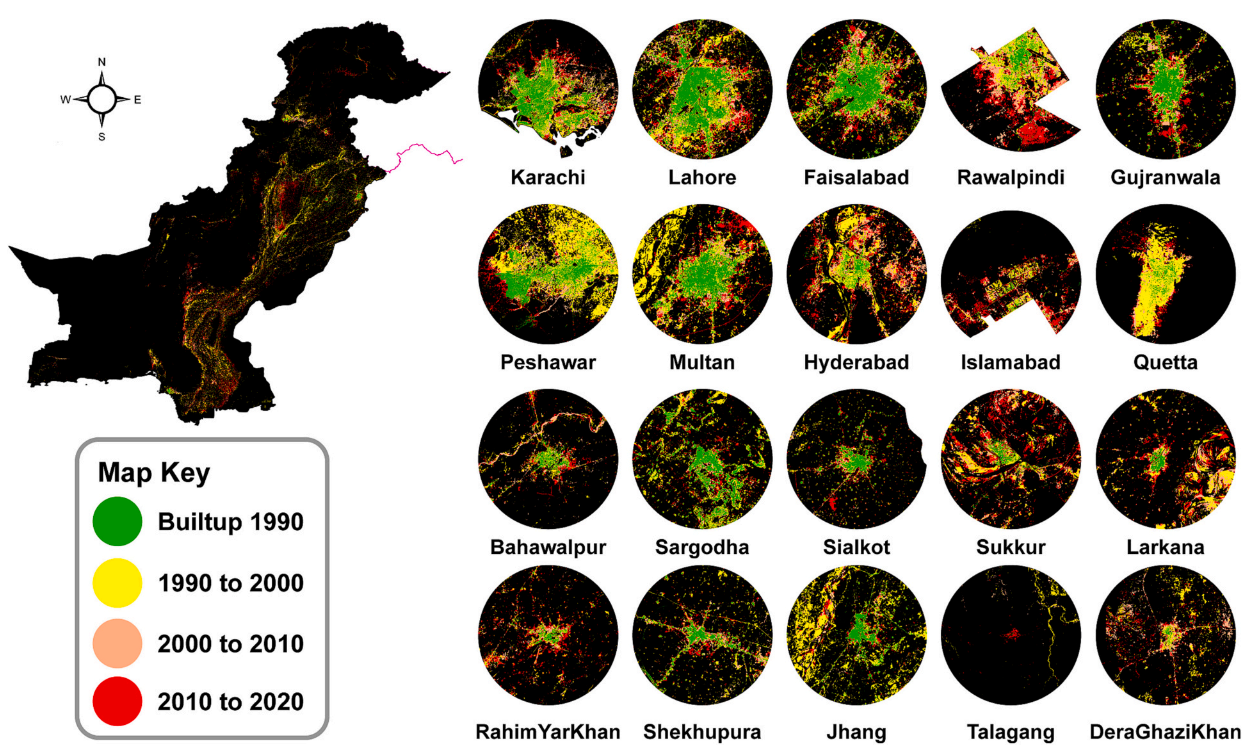

Fig. 6. Urban Sprawl from 1990 to 2020. Inset maps show the top 20 cities in Pakistan based on population.

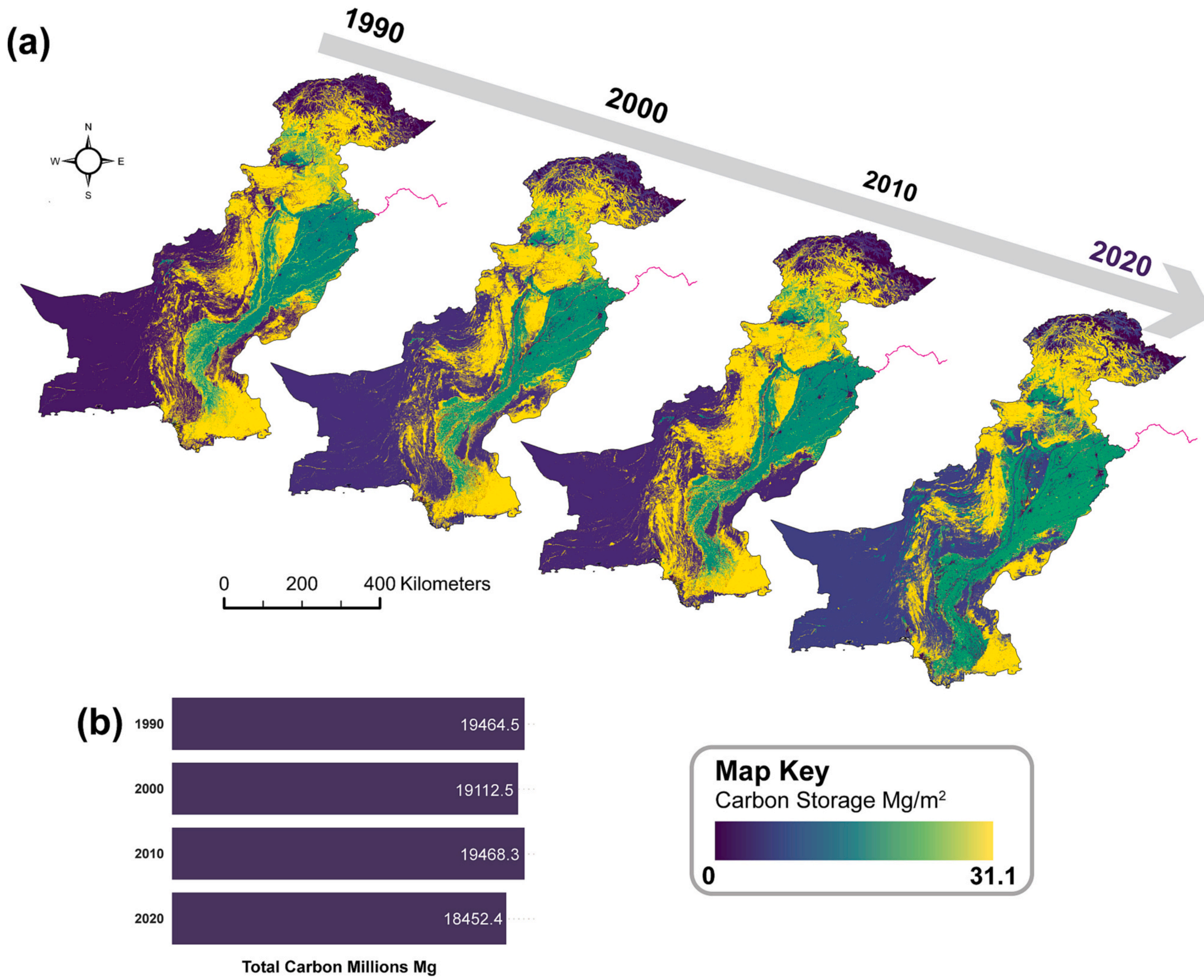

Fig. 7. (a) Total carbon storage (Mg/m^2) maps for 1990, 2000, 2010 and 2020, and (b) Total carbon in Millions of Mg each year.

drivers of carbon loss and gain in Pakistan and to develop effective strategies for mitigating climate change and preserving natural resources.

4. Discussion

4.1. Fostering remote sensing based LULC monitoring to sustain carbon storage

Urbanization and its impacts produce complex challenges for developing nations. The unplanned influx of impervious surface at the cost of green cover (i.e., grasslands and vegetation cover) results in degraded ecosystem services, and loss of carbon storage capacity is among the most significant due to its crucial role in climate regulation (Fan et al., 2022; Gao et al., 2023; Perminova et al., 2016). This study mapped high-resolution LULC change (30 m) at a national scale in Pakistan during the past three decades along with its spatial-temporal influence on terrestrial carbon storage capacity. Assessments as such provide key references to make informed decisions and policies that are imperative to sustainable development. For instance, a > 1000% increase in built-up areas during 1990–2020 should be a matter of utmost concern for the relevant authorities. These results on built-up area mapping and its growth over the past three decades are consistent with the other available comparable datasets (e.g., Gong et al., 2020; Zhao et al., 2020). This rate of built-up area influx in Pakistan is almost double that in Southeast Asia (i.e., a 518% increase during 1992–2018) as reported by Zhao et al. (2020). Similarly, in comparison with entire Asia which experienced ~90% growth during 1990–2018 (Gong et al., 2020), the built-up area increase in Pakistan is significantly higher. Based on the LULC transition analysis provided in this study (i.e., Fig. 5), the conversion of rangeland and cropland (47 and 35%, respectively) to built-up seems to be the important factor behind the reduced carbon storage capacity in Pakistan. Given the importance of cropland and rangelands for carbon sequestration and climate change mitigation (Booker et al., 2013; Deane McKenna et al., 2022; Horrillo et al., 2021; Launay et al., 2021), the regions with significant transition/conversion (Fig. 5) should be prioritized for conservation and restoration related activities. The high-resolution (30 m) intelligence provided in this study can progressively inform and support such actions at local levels. Given the rapid increase in the built-up area in Pakistan (Fig. 6) and the expected manifold global urban growth by the end of this century (Li et al., 2021), we recommend proper monitoring and informed urban planning in the country, which does not compromise the carbon storage capacity along with other environmental impacts. The remote sensing-based high-resolution dataset, such as provided here, on a national scale can provide a baseline for that along with providing insights into the assessment of grid-level long-term human-environment interactions (Li et al., 2021).

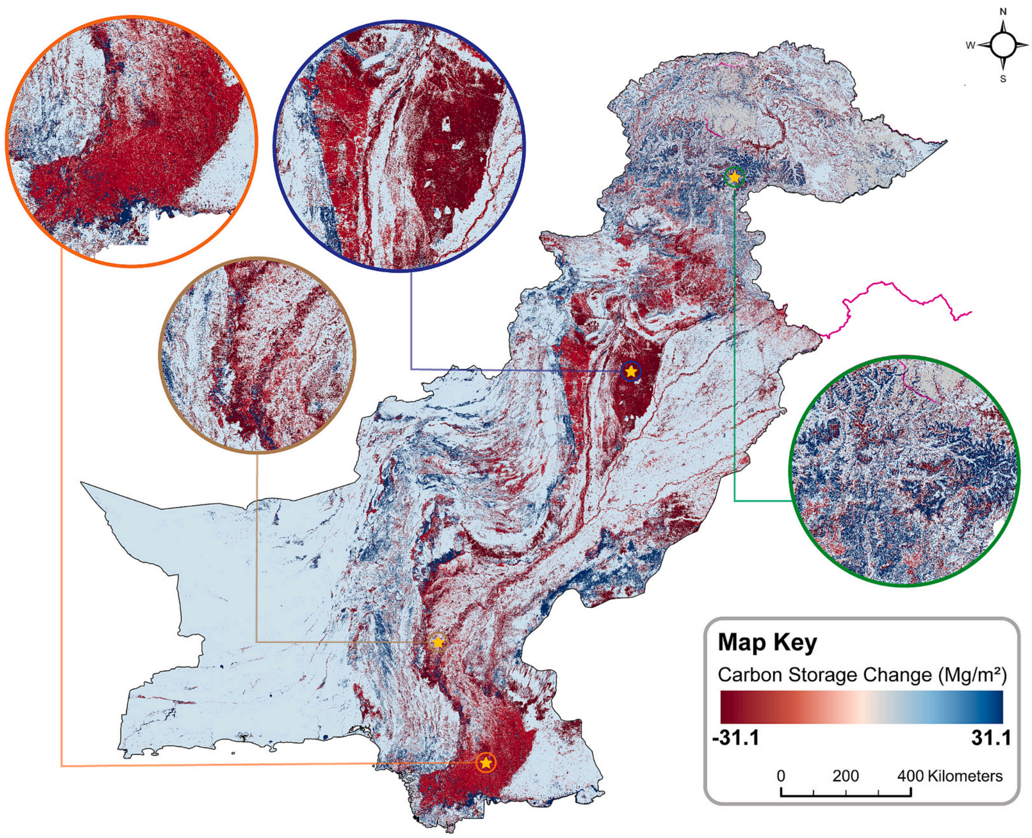

Fig. 8. High resolution (30 m) mapping of total carbon storage change (Mg/m^2) in Pakistan over the past three decades (1990–2020).

4.2. Land use land cover plays significant role in carbon storage capacity

The Global Carbon Project (available at: https://www.globalcarbonproject.org/) reported that Pakistan's CO_2 emissions increased by 2.1% in 2019, reaching a total of 199 million metric tons. This situation places Pakistan as the world's 8th largest contributor to carbon emissions, even though it is equivalent to 0.5% of global emissions. Moving forward, Pakistan's emissions are expected to increase by 50% by 2030, if no initiatives are taken to reduce them. While working on reducing emissions is one of its priorities, sustaining natural carbon sinks in Pakistan is also crucial to maintain the balance. Pakistan has lost a significant amount of its forest cover over the years, due to several factors including LULC change and natural hazards, which results in reduced carbon sink. Deforestation due to anthropogenic activities is one of the major contributors to Pakistan's increasing carbon emissions, as it releases CO_2 stored in trees and other vegetation. Connectedly, the impact of urbanization on carbon storage in Pakistan is a critical topic for sustainable development and ecosystem services. Hence, the findings and satellite data-based high-resolution mapping of LULC changes and their impact on CSD provide important references for informed planning of carbon sink in Pakistan, along with providing opportunities to manage the land resources more effectively. The results of our study showed that urban areas in Pakistan have increased exponentially over the three decades, resulting in a significant reduction in carbon storage. This reduction in carbon storage is primarily due to the conversion of natural landscapes, such as forests and grasslands, into built-up areas. The trends of growing built-up area observed in our study (as shown in Fig. 6) aligns with previous studies conducted at local scales in Pakistan (Hussain et al., 2022; Saleem et al., 2020a; Waleed and Sajjad, 2022b). While urbanization is inevitable, the re-habitation projects have slackened the urbanization issues to a greater extent in the last three decades.

4.3. Sustaining carbon pools via better land use land cover planning

Our results indicate that carbon stock has been significantly affected by urbanization, and from a geographical perspective, there has been a mix of increase and decrease in carbon stocks throughout Pakistan. The loss of carbon stock is mainly observed in/around big cities having a greater expansion of built-up areas and along the Indus River, where a significant amount of the population resides. Another significant reduction is witnessed in the southern regions along the wetland areas (Fig. 8). However, the estimated statistics show that the wetland transition to built-up is $<1\%$ (Supplementary Table S3), which ascertains that the wetland carbon pool is not that influenced in response to LULC changes in Pakistan. Urban areas have low vegetation and fewer trees (important carbon sinks), therefore, less carbon is stored in built-up regions (Hong et al., 2022). Instead, urban areas contain greater amounts of asphalt, concrete, and other non-sequestering materials (Mohajerani et al., 2017). Moreover, built-up regions have greater pollution levels, which can harm the growth of plants and trees (Saleem et al., 2020b). Ultimately, a decrease in carbon stock can be observed resulting in global warming and climate change (Kołodyńska-Gawrysiak et al., 2023; Sodango et al., 2021).

In light of the above, we recommend protecting areas with high carbon storage ability, such as rangelands, croplands, wetlands, and forests. Moreover, additional green spaces can be incorporated by identifying areas with reduced carbon storage. Therefore, sustainable land use planning and management are imperative to mitigate the negative impact of urbanization on carbon stock.

Many historical nature conservation projects in Pakistan, such as the Billion Tree Tsunami Reforestation in 2014 (Sabir et al., 2020), wetlands conservation projects by WWF (Shafi et al., 2023), and The Revival of Balochistan Water Resources Programme (RBWRP) (Ahmad, 2011) are among the initiatives that contributed to the natural landscape conservation in the country. Resultantly, despite a decrease in carbon stocks, many areas also see an increase in carbon storage. For instance, the northern regions (e.g., Khyber Pakhtunkhwa: Fig. 8) experienced an increase in carbon storage during 1990–2020. This shows the positive impact of the afforestation projects, which significantly increased forest area and hence, the carbon stock capacity in the northern region of Pakistan. These findings are in line with Goheer et al. (2023), who reported an increase of 32% in forest areas in Khyber Pakhtunkhwa during 1990–2020—increasing the carbon sink capacity of this region. According to our results, the area of forest class increased from ~21,400 Km^2 in 2010, to ~27,100 Km^2 in 2020; a nationwide increase of 26.6% over the recent decade (i.e., 2010–2020). Hence, the increase in carbon storage in northern regions is reasonable over the studied period.

However, it should be noted that despite the increase in some regions, a ~ 5% overall decrease in carbon storage is evident from this study (Fig. 7). Hence, the high-resolution mapping of carbon loss provided key information on the regions (i.e., Figs. 7 and 8), which should be prioritized for measures to establish and preserve carbon sinks in Pakistan in the face of urbanization and climate change. Similarly, the findings on LULC change and CSD provided in this study highlight the need for policies and management approaches that support sustainable urbanization, which does not compromise the carbon storage capacity of Pakistan in the face of the projected increase in its short- and long-term emissions. Such policies should focus on promoting green infrastructure, such as parks, green spaces, and urban forests, which can contribute to enhancing carbon storage and sequestration in urban areas. In short, designing and implementing sustainable land use practices and policies that prioritize carbon sequestration, such as the conservation of natural landscapes, afforestation, and reforestation, needs to be encouraged in Pakistan.

The validation of total carbon stock estimation in Pakistan poses a significant challenge due to the absence of a national-scale study. Previous studies have primarily focused on forest carbon stock assessment at a small scale, resulting in a limited understanding of carbon storage in other land use classes, such as rangeland, agriculture, and wetlands (Ali et al., 2020; Khan et al., 2020). To address this limitation, we relied on previously published literature for carbon pool values, as presented in Table 3. While these values are accurate and field-validated, variances may arise due to differences in geographical locations (Toru and Kibret, 2019). Therefore, to strengthen national-level carbon storage assessment, on-field carbon storage assessments per land use class in Pakistan are essential.

4.4. *Importance of policies and management approaches for carbon management*

The implications of this study for sustainable development and ecosystem services are significant. The analysis highlights the urgent need to adopt policies and management approaches that support sustainable urbanization and reforestation projects in order to conserve carbon storage. As the results demonstrate, urbanization has led to a reduction in carbon storage in terrestrial ecosystems, and this trend is likely to continue without intervention. Therefore, it is crucial to design and implement programs that prioritize the conservation of carbon storage while promoting sustainable land use practices. The positive impact of reforestation projects on carbon stock and forest area in the northern region further highlights the potential benefits of such initiatives. By promoting sustainable urbanization and reforestation, policymakers and managers can simultaneously address the challenges of climate change and ecosystem degradation, while also creating opportunities for sustainable development and improved ecosystem services (Canedoli et al., 2020; Jiang et al., 2023). This study provides important insights that can guide the creation of successful programs for sustainable land use and carbon management in Pakistan and can also be a useful resource for other countries facing similar challenges.

4.5. *Fostering sustainable land use practices for effective future carbon management*

The findings of this study provide important insights for future directions in sustainable land use and carbon management in Pakistan. One key direction is to prioritize policies and management approaches that promote sustainable urbanization, particularly in emerging cities that are experiencing high rates of urban sprawl (Jiang et al., 2023; Toru and Kibret, 2019). This could involve measures such as incentivizing compact, high-density urban development and discouraging the conversion of natural ecosystems to built-up areas (Wei et al., 2023; Zhang et al., 2015). Another direction is to further promote reforestation projects, particularly in regions where forest cover has declined significantly. In addition to mitigating the impact of urbanization on carbon storage, reforestation can also support the conservation of biodiversity, water resources, and other ecosystem services (Aneseyee et al., 2022). This study highlighted an increase in CSD in northern areas, primarily in the Khyber Pakhtunkhwa region, which was made possible as a result of a massive afforestation initiative done through the Billion Tree Tsunami project. Considering this, future studies can evaluate the success and failure of afforestation and conservation policies, particularly for the Billion Tree Tsunami project.

Future studies can also focus on the assessment of CSD at the local administrative level, such as district and municipal levels, which can eventually help decision-makers to understand the spatial distribution of carbon sequestration potential and identify areas with high or low carbon storage capacity. Furthermore, local-level CSD quantification will facilitate engagement with local communities, enabling collaboration and participation in carbon sequestration initiatives. Additionally, future studies can incorporate short and long terms simulated LULC scenarios (Fan et al., 2023). Short-term predicted scenarios can assist in prioritizing immediate opportunities for carbon sequestration and emission reduction, which can help in short-term interventions such as afforestation projects. On the contrary, long terms modelling scenarios, along with projected factors like population growth, land-use changes, and climate projections, can assess the long terms impacts of policy choices and development pathways on carbon storage.

Finally, there is a need to strengthen monitoring and evaluation systems to track changes in land use and carbon storage over time and to support evidence-based decision-making. By adopting such measures, Pakistan can promote sustainable land use and carbon management while also contributing to global efforts to address climate change and promote sustainable development. This study acts as a baseline for high-resolution mapping of CSD in response to LULC change in Pakistan.

5. Conclusions

Pakistan is making progress in addressing climate change, but lacks comprehensive assessment and high-resolution urbanization, and carbon storage data for informed and sustainable land use planning. To counter this, we leverage remote sensing data to assess land use transitions and their influence on carbon storage dynamics in Pakistan from 1990 to 2020. Our findings depict that since 1990, rapid change in landscape has been observed, primarily an increase in the built-up area at the cost of cropland and rangeland. This conversion compromises the carbon storage capacity in Pakistan. For instance, our findings indicate that the urban areas have expanded exponentially from ~3314 Km^2 in 1990 to ~37,786 Km^2 (an increase of ~1040%), resulting in an overall reduction in carbon storage from 19,464 Mg/m^2 in 1990 to 18,452 Mg/m^2 in 2020 (a decrease of ~ − 5%). This situation can have serious consequences in the form of increased emission levels, loss of biodiversity due to conserving of ecosystems, and reduced outcomes of climate change mitigation measures.

Overall, a rapid transition in the landscape has been observed in Pakistan, specifically from rangeland (~47%) and cropland (~35%) to the built-up class. On the contrary, some afforestation projects have increased carbon stock in northern regions of Pakistan and thus balancing the overall CSD fluctuation, somehow, in the country during 1990–2020. The study emphasizes the importance of sustainable urbanization policies and management strategies that prioritize carbon pools and contribute to national climate change mitigation goals. We further ascertain the utilization and applicability of remote sensing and earth observation data for grid-level information provisioning to support effective environmental planning and management. The high-resolution mapping of CSD presented in this study enhances our understanding of the interactions between urbanization and carbon sequestration dynamics, providing valuable insights for informed decision-making and sustainable land management practices. One of the key deliverables from this study is the grid level (30 m spatial resolution) information on CSD in response to LULC transitions, which can be useful to further determine the human-environment interactions to provide solutions which can support sustainable development. For instance, management of carbon storage capacity via informed land management practices can support the achievement of several sustainable development goals by promoting climate action (SDG 13), reducing poverty (SDG 1) and hunger (SDG 2), protecting biodiversity (SDG 15), and promoting clean water and sanitation (SDG 6).

Declaration of Competing Interest

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

Data availability

All the data used for this research are available freely and the sources are mentioned in the paper.

Acknowledgements

We are thankful to all the institutes (mentioned within the text) for the provisioning of relevant data to carry out this valuable study. The research is conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. All the data used for several analyses are freely available and the resources are mentioned within the paper. The data generated from this study (i.e., LULC and high-resolution carbon storage) will be made available through a Google Earth Engine application. Further details and information in this regard are available at https://github.com/waleedgeo/lulc_pk.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2023.107396.

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