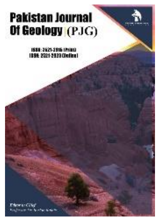
ZIBELINE INTERNATIONAL™ PUBLISHING

ISSN: 2521-2915 (Print)
ISSN: 2521-2923 (Online)
CODEN: PJGABN

Pakistan Journal of Geology (PJG)

DOI: http://doi.org/10.26480/pjg.01.2024.34.43



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RESEARCH ARTICLE

TEMPORAL ANALYSIS OF LAND USE AND LAND COVER DYNAMICS USING IMAGE CLASSIFICATION TECHNIQUES

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ARTICLE DETAILS

Article History:

Received 20 May 2024
Revised 25 June 2024
Accepted 03 July 2024
Available online 10 July 2024

ABSTRACT

In recent years, the China-Pakistan Economic Corridor (CPEC) Route has witnessed significant changes in land use and land cover (LULC) due to human activities. Understanding these changes is crucial for effective environmental management. This study focused on analyzing LULC changes between Quetta and Gwadar along the CPEC route from 2018 to 2022. Utilizing satellite data and advanced mapping techniques, particularly supervised and unsupervised image classification methods, we examined how the landscape has evolved over time. Our analysis revealed notable shifts in LULC patterns, including a decrease in water bodies, wetlands, and barren land in Quetta, alongside an expansion of built-up areas and agricultural lands. Additionally, a comparative analysis of factual data highlighted the significant changes between different regions along the CPEC route. These findings underscore the importance of monitoring LULC changes and implementing strategies to sustainably manage resources along the CPEC route.

KEYWORDS

Geographical information system, Image classification, Land Use Land Cover, Remote sensing

1. Introduction

Land use and land cover (LULC) change of any area due to human activities, are the major and central components of global, regional, local and environmental change. The Gross Domestic Product (IGDP) report indicates that the LULC that change also indicates the acme of developments in the climate ecosystem process, biodiversity factors and biogeochemical indicators (Campbell and Wynne, 2011). Therefore, it is necessary to monitor and understand the changes in environment and their related processes as it will result in such valuable and beneficial information which can be used to establish such strategies of resource management that are natural and more sustainable. Moreover, researchers emphasized on the Losses of wildlife, declining bio-diversity, Variations in the nutrient, water cycles, and carbon, desertification, deforestation, change in the composition of plant species, and uncontrolled urban growth, are other direct and indirect effects of land use and land cover changes (Congalton and Green, 2019).

Understanding land use land cover changes is also essential when trying to resolve land use disputes, particularly since population growth tends to exacerbate conflicts involving conflicting land uses. Under the effect on of anthropogenic activities, many fundamental local, worldwide and neighborhood environmental changes have been befallen in the CPEC direction, as this mission holds tremendous importance in every issue. It is vital to research as it is the LULC adjustments, critical in improving, monitoring and know-how of environmental exchange.

1.1 Study area

Quetta is the capital of the Baluchistan province and is situated at 30° 17′ 98′ N, 66°97′ 50′ E which is in the Southwest of the country, and it is the 10th most populated city of Pakistan. It is the largest and the least populated province of Pakistan by land area, bordered by provinces of Khyber Pakhtunkhwa to the north-east, Punjab to the east and Sindh to the south-east. It also shares international borders with Iran to the west and Afghanistan to the north; it is also bound by the Arabian Sea to the south. Although it makes up about 44% of the land area of Pakistan, only 5% of it is arable and is noted for an extremely dry desert climate. However, agriculture and livestock make up about 47% of Baluchistan's economy. Moreover, Baluchistan is an extensive plateau of rough terrain divided into basins by ranges of sufficient heights and ruggedness. It has the world's largest deep seaport, the Port of Gwadar lying in the Arabian Sea. Gwadar is a port city which is in out western coast of Baluchistan and is situated at 25° 6′ 18.79′ N, 62°19′ 58.87′ E. Quetta to Gwadar Western CPEC route is regarded as one of the most important socio-economic corridors for Pakistan which goes via Turbat, Hoshab and Surab and is about 903 Km long.

Quick Response Code	Access this article online	
	Website: www.pakjgeology.com	**DOI:** 10.26480/pjg.01.2024.34.43

Cite The Article: Syeda Basma, Shafi Ullah, Raja Asif Wagan, Bakhtiar Khan (2024). Temporal Analysis of Land Use and Land Cover Dynamics Using Image Classification Techniques. *Pakistan Journal of Geology, 8(1): 34-43.*

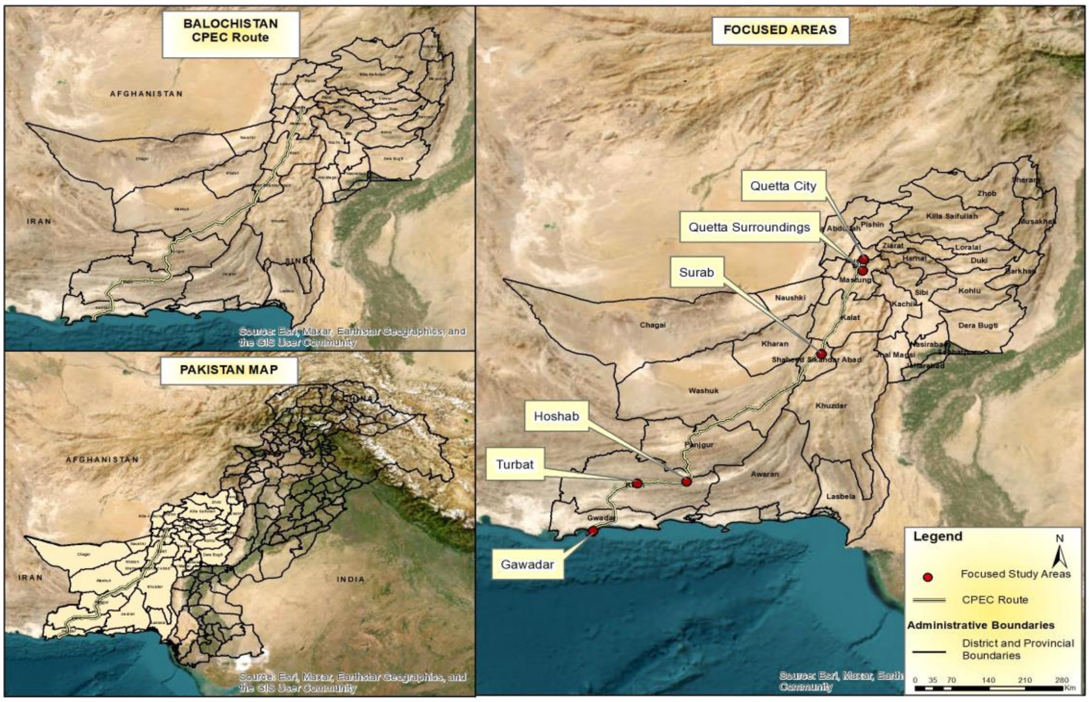

Figure 1: Route of the Study area

1.2 Problem statement

Baluchistan's Quetta to Gwadar region faces formidable challenges with regard to the dynamics of land use and land cover (LULC), marked by losses in a number of important land categories. The swift growth of infrastructure, industry, and urbanization has resulted in the deterioration and transformation of natural environments, encompassing built-up regions, shrublands, bodies of water, arid regions, and agricultural areas. The management of water resources, biodiversity preservation, environmental services, and socioeconomic well-being are all significantly impacted by these changes. However, a thorough grasp of the scope, causes, and effects of these LULC changes is inadequate, which makes it more difficult for the area's sustainable development, environmental management, and land use planning programs to be successful. Consequently, in order to address the urgent problem of LULC change from Quetta to Gwadar, research must be done immediately in order to determine the underlying causes, evaluate the losses that are associated with this change in important land categories, and create well-informed plans for reducing negative effects and fostering resilient land use practices.

1.3 Objectives of the study

- To evaluate the land use and land cover (LULC) changes from Quetta to Gwadar in Baluchistan during the last ten years in terms of spatiotemporal patterns.
- To determine and measure losses in the research area's built-up regions, shrublands, water bodies, desolate areas, and agricultural lands.
- To look at the underlying causes and drivers of the observed LULC changes, such as infrastructure improvements, industrial development, urban growth, and agricultural practices.
- To examine how LULC modifications may affect the region's socioeconomic livelihoods, water resources, conservation of biodiversity, and ecosystem services.
- Extending the study for further research

a. To evaluate how well-adjusted current land-use policies, rules, and management techniques mitigate negative effects and encourage ecological land-use practices.

b. To create suggestions and plans for enhancing environmental management, land use planning, and sustainable development programs in order to tackle the difficulties brought about by LULC modifications in Baluchistan, especially along the Quetta to Gwadar corridor.

2. Related Literature

Improved water conservation strategies may be produced by having a clear understanding of the geographical and temporal changes taking place in a watershed over time, as well as the interactions among the watershed's hydrological factors (Ashraf, 2013; Butt et al., 2015; Othman et al., 2014) . A study assesses possible implication of the input data which can be used for the betterment of the land through an unsupervised technique (Macarringue et al, 2022). The outcome of the study shows an uplift greenery and vegetation during 1976, 1990 and 2002 and the increment was witnessed in water bodies in 1990 while the decline was witnessed during 2002.

A study in 2019 confirms that the LULC change is higher and over the scale which can be damaging aspects of ecosystem's functions are ignored (Munthali et al., 2019). The aim of the study was to demonstrate primary tools, data and approaches required for analysis, mapping and assessing the LULC and to investigate about the challenges and limitations that may influence the performance in future. Another research was conducted for Dedza district of Malawi in which geospatial techniques and remote sensing was used to detect LULC multi temporal changes, and the results discloses that the wetlands, water bodies and the agricultural land was extremely reduced while the build-up areas and the barren lands are increased to a large extent between 1991and 2015 (Munthali et al., 2019). Images with high spatial, temporal, radiometric and spectral resolution, allow the mapping of large areas in a relatively short time. A group of researchers reinforced the improvement of techniques and algorithms, which allowed the automation of the mapping, with reliable results (Munthali et al., 2019; Mutanga and Kumar, 2019; Liu et al., 2021). Additionally, another researchers used remote sensing and GIS system techniques on geospatial LULC change by modelling maps and agent based LULC demonstrations (Mallupattu and Sreenivasula Reddy, 2013).

However, to perform LULC analysis, the remote sensing GIS methods and strategies for change detection have increasingly been applied with archived datasets which has brought the development as well as evaluation of different strategies for the detection of change with analysis and detection of land use land cover modifications [30]. These strategies were reviewed appreciably together with the availability of comprehensive summaries by (Haque and Basak, 2017). Temporal resolutions, thematic resolutions, spectral resolutions, and spatial resolutions of the information of vegetation obtained using remote sensing effected the digital detection of change thus making appropriate choice of change detection technique an essential aspect of outcomes (Roy and Roy, 2010; ZHANG et al., 2019). By using different methods of detection of changes, different alternate detection maps are produced such as superior models, GIS processes, algebra, visual analysis, classification, transformation, and other tactics are the seven categories under which trade detection strategies can be categorized. Researchers applied a well-

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known and adaptable approach of detection for LULC change from images with numerous spectral and spatial resolution are collected through several sensors which continues to be post class comparison (Yao et al., 2019; Carranza-García et al., 2020). The method is cantered on the detection inside the land cover as well as the development of maps that display the entire matrix of changes through the primary and second iterations of spectral categorization the use of evaluating segments to segments or pixels to pixels (Costache et al., 2019). Analysts define the instructions of LC's post class evaluation technique with the aid of supervised and unsupervised algorithms. A study concluded that the submit-29 class evaluation method's character pixel categorization reduced the geometrical, radiometric, sensor, and atmospheric variances among dates (Pande et al., 2021). Although, each knowledge and time remain vital for spotting the post class evaluation.

Table 1: Summary of the related Literature in image classification technique in LULC

Ref	Study Area	Data Source	Image Classification Technique	Accuracy Assessment Method	Key Findings	Limitations
(Ashraf, 2013)	Himalayan watershed	Hydrological data, satellite imagery	Not specified	Not specified	Changing hydrology due to climate change	Lack of specific image classification details
(Butt et al. 2015)	Simly watershed, Islamabad, Pakistan	Landsat imagery	Supervised classification	Overall accuracy, Kappa coefficient	Significant land use change; urbanization major factor	Limited satellite imagery resolution
(Campbell, and Wynne, 2011)	Various global locations	Multiple satellite and aerial imagery sources	Various techniques (supervised, unsupervised, object-based)	Error matrix, Kappa coefficient, user's and producer's accuracy	Comprehensive introduction to remote sensing principles	Broad overview, lacks specific case study details
Carranza-García, M., et al. (2020)	Autonomous vehicle environments	Camera data	One-stage and two-stage object detectors	Mean Average Precision (mAP)	Two-stage detectors outperform one-stage detectors	Specific to autonomous vehicles
(Comber, et al., 2012)	Various landscapes	Remote sensing imagery	Multiple techniques	Spatial analysis of classification accuracy	Spatial autocorrelation impacts accuracy assessment	Requires advanced statistical understanding
(Congalton, and Green, K., 2019)	Not specified	Various remote sensing data sources	Various techniques	Error matrix, Kappa coefficient	Comprehensive guide on accuracy assessment principles	Theoretical focus, lacks specific case studies
(Costache, et al., 2019)	Flash-flood susceptible areas	Remote sensing and GIS data	Multi-criteria decision making, machine learning	Validation with historical flood data	Effective assessment of flash-flood susceptibility	Dependent on quality of historical data
(Ashraf, 2013)	Himalayan watershed	Hydrological data, satellite imagery	Not specified	Not specified	Changing hydrology due to climate change	Lack of specific image classification details
(Butt, et al. 2015)	Simly watershed, Islamabad, Pakistan	Landsat imagery	Supervised classification	Overall accuracy, Kappa coefficient	Significant land use change; urbanization major factor	Limited satellite imagery resolution

3. Methodology

There are different types of methods that are available to get satellite imagery for LULC analysis. In this study Google Earth Engine (GEE) has been used, which provides access to interactive maps, satellite imagery and spatial databases of a desired area, there are some more GIS data sources available like FAO map catalogue, USGS etc. that are open source and has been used earlier as well in combination with ArcGIS version 10.8. To find, add and organize maps and to do map images classifications. Furthermore, a set of supervised has been used to process satellite images. With the help of Google Earth Engine extraction of desired reference data has also been done. In the end, the overall accuracy is found using the kappa coefficient matrix system. Figure 2 illustrates the whole process used in this research study to derive statistics on the area's multi-temporal land use and land cover analyzation.

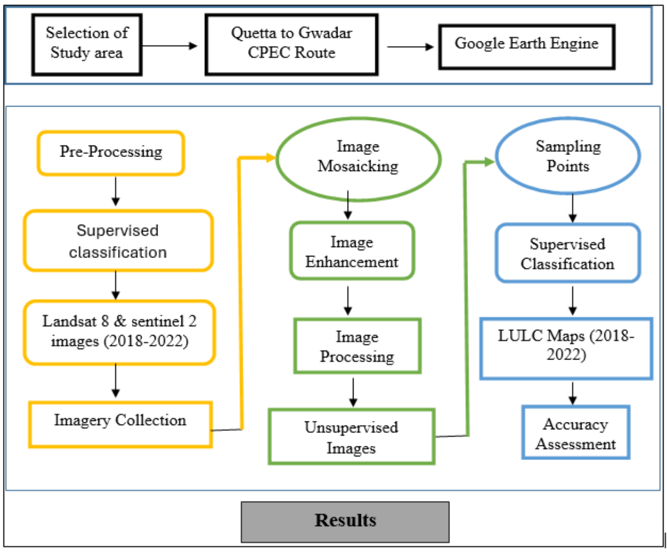

Figure 2: Process Flow of LUCL in this case study

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3.1 GIS tools utilized

The following tools and software were used during the execution of this research study.

- Google Earth Engine for geospatial analysis software to view and examine imagery from satellites. It is used by researchers and non-profit organizations for a variety of tasks, including managing natural resources and anticipating disease outbreaks.
- ArcGIS 10.8 to manage and get information from imagery and other remotely sensed data. It offers access to the greatest library of images in the world as well as imagery tools and procedures for visualization and analysis.

3.2 Preprocessing of satellite imagery

Characteristics of the two satellites Landset8 and Sentinal2 are shown in Table 3. The preprocessing methods are essential for preparing satellite imagery for analysis and extracting meaningful information about land cover and land use dynamics in the study area. includes the following steps:

- The first procedure, called geometric correction, fixes imperfections in satellite imagery and guarantees that the spatial relationships between picture pixels accurately reflect their respective places on Earth's surface.
- Assigning coordinates (latitude and longitude) to the pixels in the satellite imagery is the second phase, or geo-referencing. As a result, it is possible to spatially align the photos with other geographic information and maps.
- Using an image extraction approach, the third stage entails removing particular features or areas of interest from the satellite imagery so they may be further analyzed. This involves taking agricultural land, bodies of water, and land use classes.
- Topography modifications are made to account for differences in the altitude of the land. This lessens distortions brought on by slope effects and terrain shadows by ensuring that pixel values remain constant at all elevation levels.
- After that, image enhancement techniques are used to highlight particular elements in the satellite imagery by changing brightness, contrast, and color balance. This improves the satellite imaging's visual quality and interpretability.
- To choose a more manageable region of interest (ROI) from the bigger satellite image dataset, sub-setting is required. By concentrating the analysis on elements found in the research region, processing time and computational complexity are decreased.
- The final phase, layer stacking, applies various bands or spectral channels from the satellite imagery into a single, multi-layered image dataset for a more thorough examination and understanding.

All the image preprocessing methods as described (geometric correction, geo referencing, extraction, atmospheric correction, topography correction, image enhancement, sub-setting and layer stacking) were carried out using ArcGIS 10.8.

3.3 Data collection and image processing

This study uses Sentinal-2 and Landsat 8 (OLI) satellite data, and the images were chosen based on their quality and availability. To minimize the impacts of seasonality and changing light positions, the photographs were taken throughout the same yearly season.

- Landset8: Images from the Landsat 8 (OLI) Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) have a spatial resolution of 30 meters for each of the nine spectral bands.
- Sentinal2: Wide-area, high-resolution, multispectral imaging mission Sentinel-2 (S2) has a global 5-day revisit frequency. In this investigation, the S2 Multispectral Instrument (MSI), which samples 13 spectral bands at a resolution of 10 meters, was used. The specific details of the data used in this research study are shown in Table 1.

Table 1: Details of satellite imagery from Google Earth Engine

Satellite	Sensor	Path/Row	Spatial resolution (m)	Date of acquisition
Landsat 8 & Sentinel	OLI	168/070	30/10	2018-01-01
Landsat 8 & Sentinel	OLI	168/070	30/10	2019-01-01
Landsat 8 & Sentinel	OLI	168/070	30/10	2020-01-01
Landsat 8 & Sentinel	OLI	168/070	30/10	2021-01-01
Landsat 8 & Sentinel	OLI	168/070	30/10	2022-01-01

3.4 Characteristics of Landsat images used for the study.

Using the two satellite pictures, typical image processing methods such as geometric correction, geo referencing, extraction, atmospheric correction, topography correction, image enhancement, sub setting and layer stacking (combination and band selection), were carried out using ArcGIS 10.8. (Clipping).

3.5 Data collection

For this research, multispectral satellite imagery from Landsat-8 and Sentinel-2 satellites was collected covering the Quetta to Gwadar CPEC route for the years 2018 to 2022. These datasets provide a temporal sequence of imagery capturing land cover changes over the specified five-year period.

3.5.1 Unsupervised classification

To initiate the analysis, an unsupervised classification technique was applied to satellite imagery. Unsupervised classification involves grouping pixels with similar spectral characteristics into clusters, without the need for predefined training samples. This step helped identify potential land cover classes present in the study area.

3.5.2 Refinement of unsupervised data

The unsupervised classification results were refined to improve accuracy and reduce misclassification. Post-classification processing techniques were applied to the clustered segments. This process involved identifying and correcting misclassified pixels to achieve a more accurate representation of land cover classes.

3.5.3 Supervised Classification

To further improve the classification accuracy and obtain more specific land cover categories, a supervised classification approach was used. In this step, representative training samples were carefully selected across the study area, each associated with a known land cover class. These training samples were used to train a classification algorithm, such as Maximum Likelihood or Support Vector Machine, to classify the entire dataset into distinct land cover categories.

3.6 Image classification

Table 2 lists the classes and their descriptions. The Image classification is the classification of an image into fewer distinct classes based on reflectance values. The images were classified using the historical function of Google Earth, visual interpretation of each LULC class, supplemental information, the researcher's local expertise, and physiographic understanding of the study region.

3.6.1 Image accuracy evaluation

Accuracy of classification is the degree of agreement between an image's categorization and ground-based reference data. For providing a generic map quality measurement on which to base the evaluation of algorithms for change reduction, the classification accuracy is assessed. Also, it helps with understanding by pointing out classification or classification-related problems. When there are discrepancies in between real class classification errors appear on the map's classified data as well as the actual class on the set of validations for the field or ground reference.

Error metrics, often known as a confusion matrix, are used to define classification error or accuracy. The relationship between the relative results and reference data produced by automated categorization is assessed by the error matrix, by category. Most of the metrics employed to evaluate assessment accuracy are error metrics or confusion metrics, which are based on the user's intentions. The Kappa coefficient, in (equation 4), Producer's accuracy (PA), in (equation 3), Overall accuracy (OA) (equation 2), and User's accuracy (equation 2) are the commonly used metrics for accuracy statistics and their bases on the error matrix of picture categorization from remotely sensed data, according to Congalton and Green and Comber, Fisher, Brunsdon and Khmag (UA)

It is calculated by dividing the total number of evaluated pixels by the total number of correctly identified pixels. Based on data from remote sensing imagery, producer accuracy indicates how effectively the map's creator categorized the various types of land cover. The user's accuracy demonstrates how well the scholar can utilize the maps to distinguish between various forms of ground cover. In (equation.4), the Kappa coefficient determines the discrepancy between the possible agreement and the real agreement based on the map and the verification of ground data. In comparison to maps with lower classification accuracy, those with high classification accuracy are more valuable for land use planners and administrators. A value of 0.80 indicates excellent agreement and good accuracy, a value of 0.40 to 0.80 indicates moderate agreement, and a value of less than 0.04 indicates poor agreement. Keep in mind that values for the Kappa coefficient range from 0 to 1, with a value of 0.80 indicating excellent agreement and good accuracy. The equations for OA, PA, and UA are as follows:

$$\text{Overall accuracy} = \frac{Sum\ of\ diagonal\ tallied\ (correctly\ identified)}{Total\ number\ of\ samples} \times 100 \quad (1)$$

$$\text{User's accuracy} = \frac{Samples\ correctly\ identified\ in\ the\ row}{Total\ row} \times 100 \quad (2)$$

$$\text{Producer's Accuracy} = \frac{Samples\ correctly\ identified\ in\ the\ column}{Total\ column} \times 100 \quad (3)$$

$$\text{Kappa Coefficient (K)} = \frac{Observed\ accuracy\ (P_o) - Chance\ agreement\ (P_e)}{total\ number\ of\ samples} \times 100 \quad (4)$$

Where the observed accuracy (P0) is calculated using the diagonal of the error matrix, and the chance agreement (Pe) is integrated off the diagonal sum of the product of the row and column totals for each class.

Table 4: Image classification in LULC classes with description

LULC class	Description
Water bodies	Rivers, lakes, ponds, reservoirs, and permanently open water
shrubs	Permanent and seasonal small grass patches/grass lands along the lake, or in barren land etc.
Agricultural land	All cultivated and uncultivated agricultural lands areas such as farmlands, crop fields including fallow lands/plots and Horticultural lands.
Hilly area	Hills or mountains beside the road.
Built-up area	Residential, commercial, and industrial space, as well as mixed-use and other urban areas, socioeconomic infrastructure, airport and roads.
Barren land	Un vegetated or sparsely vegetated regions surrounding and inside forest protected areas, including exposed soils, stock quarries, boulders, landfills, and active excavation zones.

3.6.2 Confusion matrix

Classification error or accuracy is defined as error metrics which is also defined as confusion matrix (Comber et al., 2012; Congalton and Green, 2019). The error matrix compares the connection between the known reference data and the relative results produced by automated categorization on a category-by-category basis. The bulk of the metrics used to gauge assessment accuracy are based on confusion metrics or mistake metrics, which depend on the user's intentions. The Kappa Coefficient, Producer's Accuracy (PA), Overall Accuracy (OA), and User's Accuracy are the generally used metrics for accuracy statistics and their bases on the error matrix of picture categorization from remotely sensed. Overall, the confusion matrix provides a comprehensive understanding of the classification model's performance for each class. It enables remote sensing practitioners and analysts to assess the effectiveness of automated image categorization methods and make informed decisions based on the accuracy statistics, as shown in Table 4.

3.6.3 Temporal analysis approach

The following procedures are part of the technique for studying changes in Land Use and Land Cover (LULC) that uses the temporal analytical approach:

- Using techniques like image differencing and multitemporal classification, change detection techniques were applied to compare LULC properties over time. This allowed for the identification of change areas as well as the measurement of change's magnitude and direction.
- Examined the temporal trends in LULC changes from 2018 to 2021 to pinpoint trends, trajectories, and change rates. The importance of temporal patterns in land cover dynamics was evaluated by the application of time series analysis.
- To guarantee the validity of the temporal analysis approach and raise the study's credibility, validate the temporal analysis results using actual data to evaluate the findings' correctness and dependability.

4. Accuracy Assessment

To calculate the overall accuracy rate (OA) rate, the Kappa Coefficient, the user's accuracy (UA), and the producer's accuracy (PA), which are all important considerations when providing error analysis and assessing classified maps, the results of the change detection and confusion matrices were used. These measures are frequently used to assess the precision and caliber of change detection, a remote sensing product that also includes target detection and categorization. Verify that the training and testing groups' pixel counts for each class were equivalent.

In addition, the test data-derived confusion matrix was used to evaluate the classification accuracy. To calculate the overall classification accuracy and the kappa index, we used the data from the confusion matrix for the years 2018–2022. In 2018, the classification accuracy was 87.4% overall, according to the Kappa score of 0.87. Overall, with a Kappa value of 0.879, the classification accuracy for 2020 was 88.4%. In contrast, the Kappa index was 0.95 in 2022, and the overall classification accuracy was 95.7%. It's also important to note that figures for the relevant years were derived for both user accuracy and producer accuracy. These figures are broken out as follows for the year 2018: 88.4% of barren land covered; 85.4% of land used for barren land; 90.1% of land covered in built up areas; 78.3% of land used for agriculture (water body is 82.4%). The accuracy of producers varied from 81.4 percent (agricultural) to 90.1 percent (Shrubs) in 2020, while the accuracy of users ranged from 90.1 percent (Built up Area) to 91.5 percent (Shrubs). In a discussion that takes place in the year 2022, it is made abundantly clear that the accuracy of the producer was located between 94.2% (Built up Area) and 100% (Barren land), whereas the accuracy of the user was in the 94.5 percentile (agricultural).

Table 5: Accuracy Assessment of classification

Image Year	Class	Reference Totals	Classified Totals	Number Correct	Producer`s accuracy	User`s accuracy
2018	Built-up	60	45	50	91.3	90.1
	Water Body	40	46	36	75.5	82.4
	Barren land	55	55	45	85.8	85.4
	Shrubs	60	47	55	95.4	96.4
	Agriculture	40	48	38	80.5	78.3
	Total	**255**	**241**	**224**	-	**87.4**
2019	Built-up	65	45	58	92.2	91.2
	Water Bodies	41	49	40	86.1	85.2
	Barren land	59	50	56	86.7	93.7
	Shrubs	65	49	60	91.8	92.7
	Agriculture	50	48	45	93.3	90.4
	Total	**280**	**241**	**259**	-	**87.3**
2020	Built-up	70	44	65	90.2	90.1
	Water Bodies	44	35	41	100.0	88.2
	Barren land	60	46	55	79.1	74.9
	Shrubs	67	42	60	90.1	91.5
	Agriculture	44	38	38	81.4	91.6
	Total	**285**	**205**	**259**	-	**88.4**
2021	Built-up	76	48	70	93.2	92.1
	Water Bodies	46	38	39	95.0	90.2
	Barren land	70	49	65	95.1	89.3
	Shrubs	40	40	39	88.1	87.5
	Agriculture	45	37	42	85.4	93.6
	Total	**277**	**212**	**255**	-	**91.7**
2022	Built-up	85	50	80	94.2	95.1
	Water Bodies	80	51	79	100.0	96.2
	Barren land	75	52	74	100.0	94.9
	Shrubs	40	39	37	81.1	80.5
	Agriculture	49	54	48	99.4	94.5
Total		**329**	**246**	**318**	-	**95.7**

Initially, the unsupervised classification is used to generate clustered segments based on spectral similarities in satellite imagery. However, these clusters needed refinement to achieve higher accuracy and specificity in land cover classification. To refine the unsupervised data, post-classification processing techniques are applied. This involved comparing the unsupervised results with ground-based reference data or field observations to identify misclassified pixels. Additionally, misclassifications are then corrected to ensure that each cluster accurately represented a specific land cover class. Moreover, the refined data, along with the ground-based reference data, are then used to create a set of training samples for supervised classification. Each training sample represented a known land cover category. The supervised classification algorithm is trained on the dataset to classify the entire satellite imagery into the different land cover classes. This process enhanced the accuracy of the final land cover map and provided more meaningful results for the LULC change analysis.

4.1 Results for LULC changes

Accurate and current data on land cover change are necessary for a thorough understanding and assessment of the environmental effects of such changes. Using such data is predicated on the need of distant sensing information for change identification in the "from-to" analysis. In this investigation, GIS and RS software were utilized to map out various LULC types and assess the amount to which they changed from 2018 to 2022. Figure 8 and 9 shows the pictorial and numerical changes of Multi temporal analysis of past five years has been expressed very clearly since 2018 to 2022. Moreover, LULC changes of Gwadar 2018, 2019, 2020, 2021 and 2022 are shown in Figures 3, 4, 5, 6, 7 and 8, respectively.

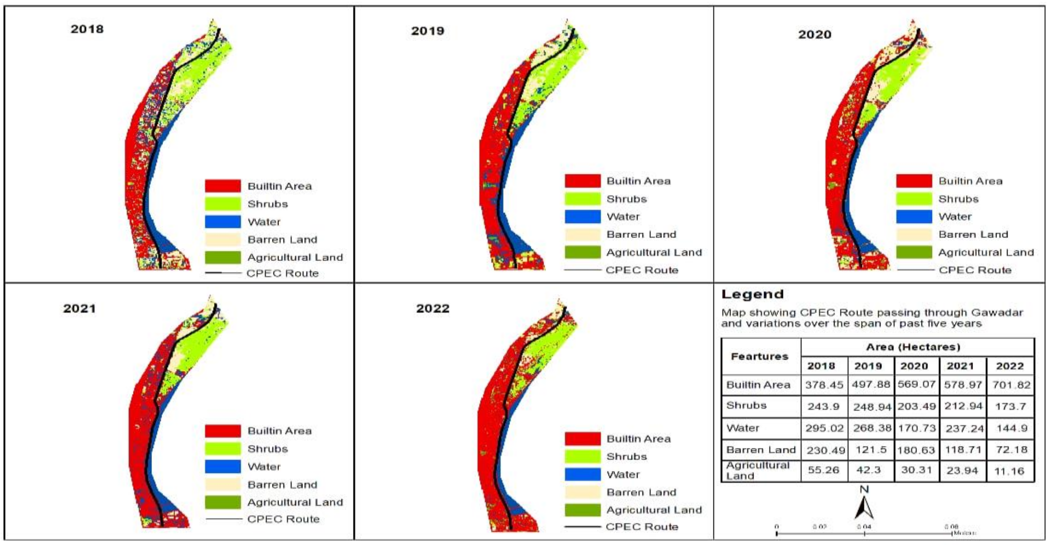
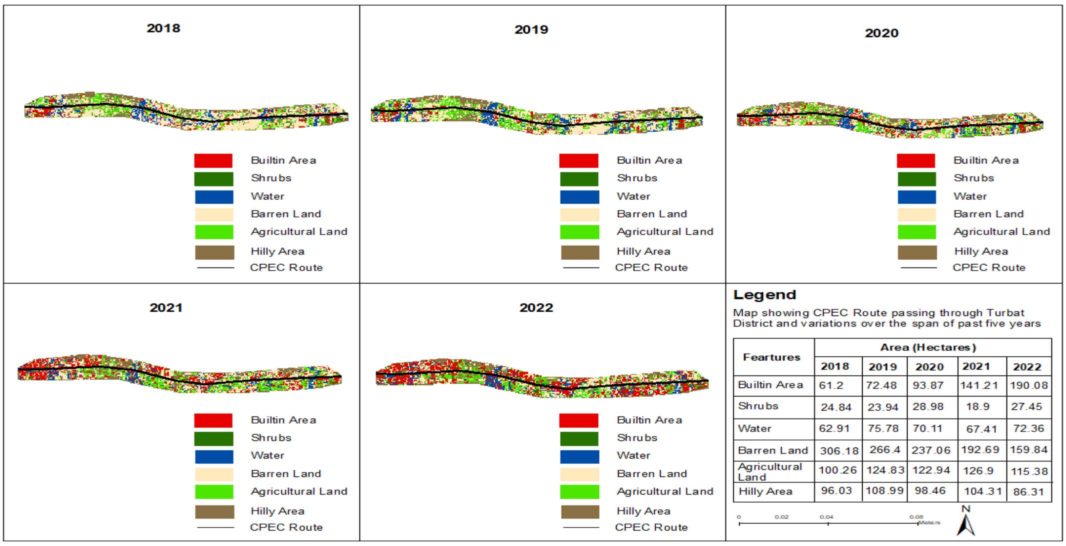


Figure 3: LULC changes of Gwadar 2018, 2019, 2020, 2021 and 2022

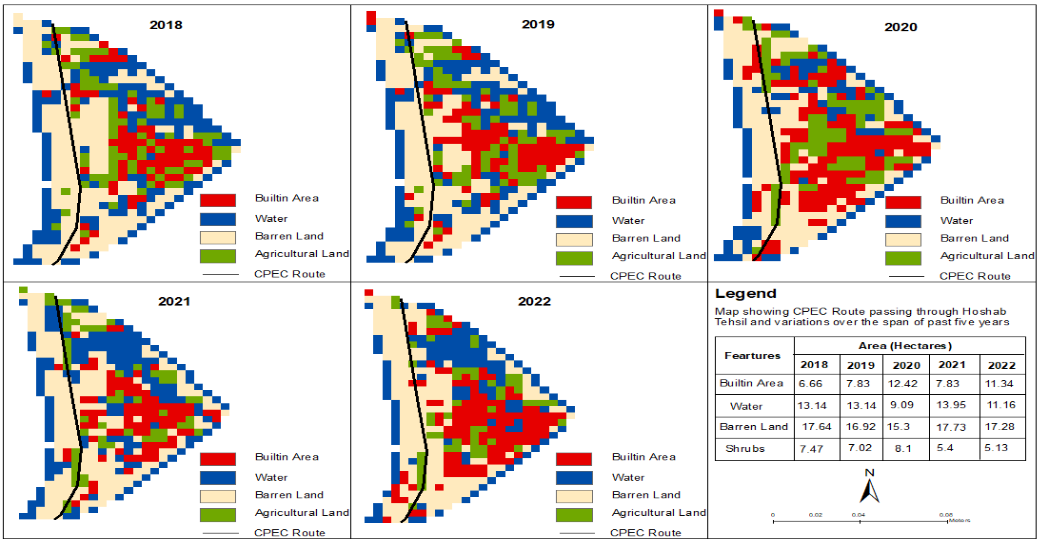
Figure 3 shows Land cover/Land use changes of Turbat in 2018, 2019, 2020, 2021 and 2022 are shown which depicts multi temporal change majorly in built-up area and barren land visually in the span of past five years.



Feartures	Area (Hectares)				
	2018	2019	2020	2021	2022
Builtin Area	61.2	72.48	93.87	141.21	190.08
Shrubs	24.84	23.94	28.98	18.9	27.45
Water	62.91	75.78	70.11	67.41	72.36
Barren Land	306.18	266.4	237.06	192.69	159.84
Agricultural Land	100.26	124.83	122.94	126.9	115.38
Hilly Area	96.03	108.99	98.46	104.31	86.31

Figure 4: LULC changes of Turbat 2018, 2019, 2020, 2021 and 2022

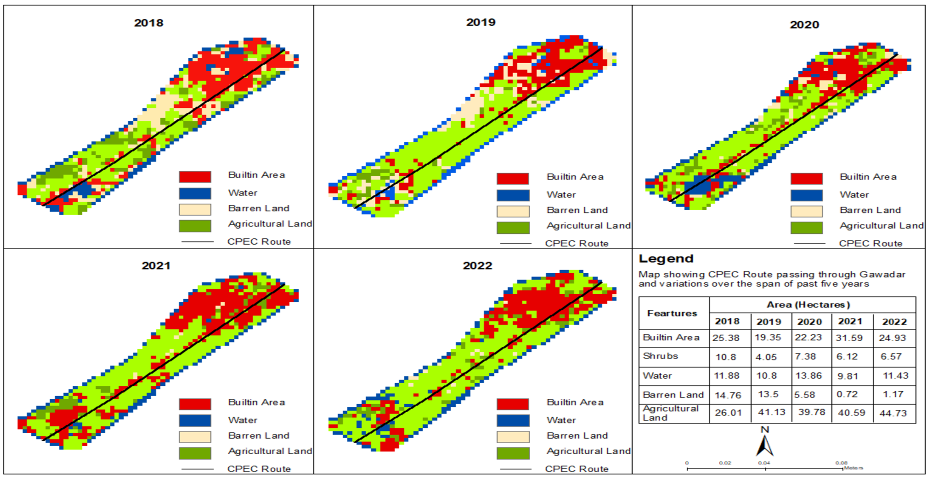
Similarly, Figure 4 shows Land cover/Land use changes of Hoshab 2018, 2019, 2020, 2021 and 2022 are shown in which the variations in tehsil of Hoshab in past five years can be clearly noted.



Feartures	Area (Hectares)				
	2018	2019	2020	2021	2022
Builtin Area	6.66	7.83	12.42	7.83	11.34
Water	13.14	13.14	9.09	13.95	11.16
Barren Land	17.64	16.92	15.3	17.73	17.28
Shrubs	7.47	7.02	8.1	5.4	5.13

Figure 5: LULC changes of Hoshab 2018, 2019, 2020, 2021 and 2022

Figure 5 shows Land cover/Land use changes of Surab 2018, 2019, 2020, 2021 and 2022 are shown which illustrates the variations majorly in buildup and agricultural area in tehsil of Surab in past five years.



Feartures	Area (Hectares)				
	2018	2019	2020	2021	2022
Builtin Area	25.38	19.35	22.23	31.59	24.93
Shrubs	10.8	4.05	7.38	6.12	6.57
Water	11.88	10.8	13.86	9.81	11.43
Barren Land	14.76	13.5	5.58	0.72	1.17
Agricultural Land	26.01	41.13	39.78	40.59	44.73

Figure 6: LULC changes of Surab 2018, 2019, 2020, 2021 and 2022

Figure 6 shows Land cover/Land use changes of Quetta 2018, 2019, 2020, 2021 and 2022 where multi temporal changes in Quetta bypass in the span of past five years are illustrated.

Moreover, Figure 7 shows Land cover/Land use changes of Quetta City 2018, 2019, 2020, 2021 and 2022 are shown in which we can clearly see the multi temporal changes in terms of built-in area, water level variation and agriculture land cultivation in Quetta city in the span of past five years.

5. Discussion

The LULC changes during the study region's effects over the last five years can be traced to both human activity and local and national legislation, which have led to an increase in built-up areas and bare land. When more arable land is lost to the expansion of populated regions and the construction of infrastructure, Food security and the availability of forest products and services are impacted by the vast the largest portion of agricultural land that has been turned into buildup areas. To address the concerns of forest degradation and deforestation, the expansion of urban or built-up areas, to stop the loss of wetland areas agricultural land, and water bodies in this research region, forest management, environmental groups, lawmakers, along with stakeholders must move quickly. Moreover, to comprehend the LULC changes that occurred along the CPEC route, this research presents LULC change information. From Quetta to Gwadar, which is 903KM long, planners, academics, environmentalists, and other stakeholders will be able to use the information to make critical planning decisions for the sustainable use of natural resources in Baluchistan. Based on the study's findings, it is advised that further research be done to determine the root reasons and proximate causes of the LULC change in the study area.

Additionally, it is recommended that suitable measures be taken by those in charge of making decisions in the study region to safeguard and restoration of the forests, and creation of plans for managing natural resources for Baluchistan's sustainable development projects. The results discussed in the previous sections offer crucial planning tools for environmentalists, stakeholders, and planners, facilitating effective management of the CPEC route and other development projects. As Baluchistan stands to benefit from the CPEC project, our study emphasizes the significance of responsible land use planning and resource management for the province's long-term prosperity.

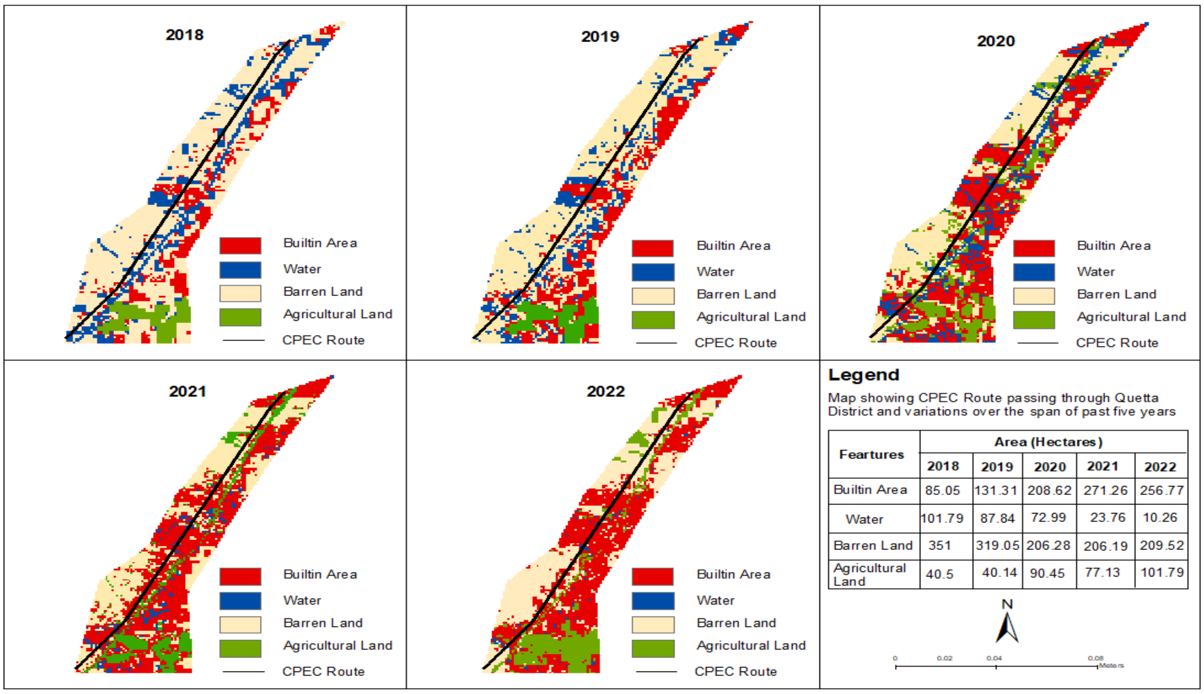


Figure 7: LULC changes of Quetta city 2018, 2019, 2020, 2021 and 2022

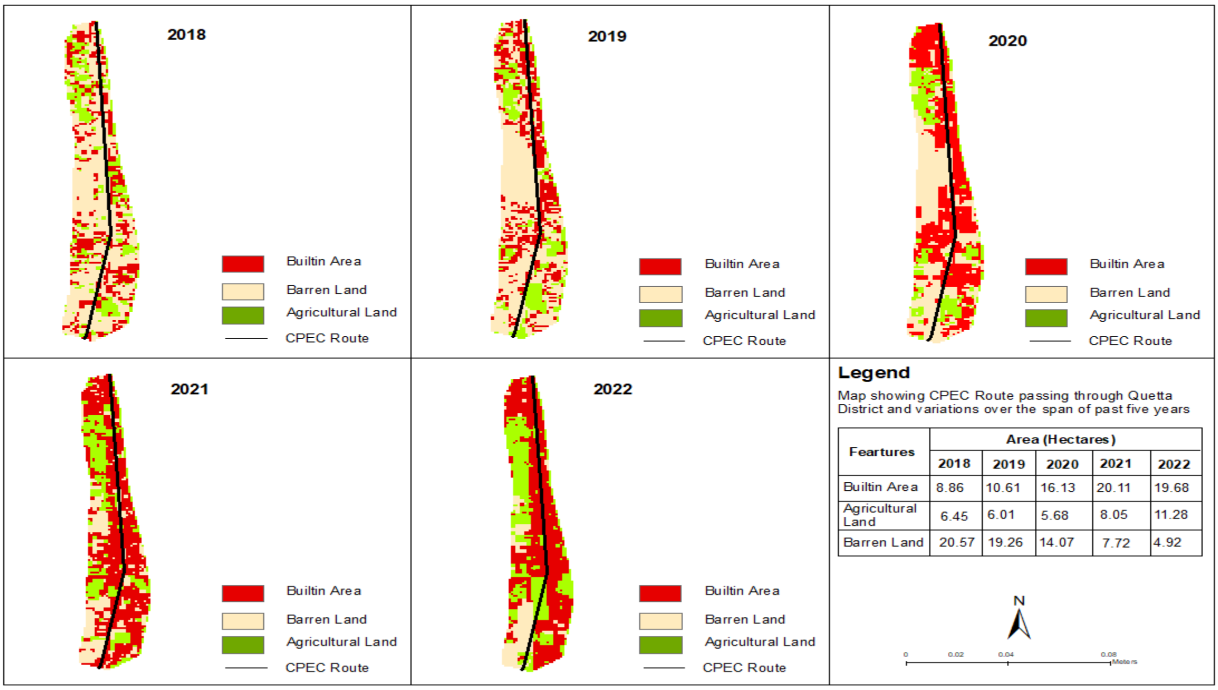


Figure 8: LULC changes of Quetta City 2018, 2019, 2020, 2021 and 2022

Moreover, the accuracy assessment demonstrated the reliability of the classification, with high producer accuracy values ranging from 81.4% to 100% for different land cover classes. User accuracy values ranged from 90.1% to 94.5%, showcasing the efficiency of the maps in distinguishing between various ground cover types. Moreover, the results provide valuable insights into LULC changes along the Quetta to Gwadar CPEC route, aiding informed decision-making for sustainable development and environmental preservation. The integration of remote sensing and GIS techniques proved effective in accurately detecting land cover changes, supporting responsible land use planning for the region's socio-economic growth. By leveraging Geographical Information System and advanced remote sensing technologies, we can continue to monitor and assess environmental changes, contributing to strategies for ecological protection and the preservation of natural resources. This research contributes to creating a more sustainable and resilient CPEC route, serving as a valuable reference for decision-makers shaping the future of Baluchistan's development. The study offers insightful information about the dynamics of LULC changes throughout the previous five years (2018 to 2022) along the China-Pakistan Economic Corridor (CPEC) route from Quetta to Gwadar. This research demonstrated the efficacy of our approach for detecting LULC changes in the study region by achieving considerable increases in overall classification accuracy using a combination of supervised and unsupervised image classification approaches.

The findings show a notable rise in classification accuracy from 87.4% in 2018 to an astounding 95.7% in 2022, highlighting the stability and dependability of the used methodology. Numerous reasons, such as improved classification algorithms, more training data, and developments in remote sensing technologies, are responsible for this improvement. The high accuracy of classification attained boosts the validity of the study's conclusions and increases assurance in the LULC modifications that were found.

Furthermore, a comparison of Quetta's LULC changes with those of Gwadar, Turbat, and Hoshab showed notable decreases in the area's wetlands, water bodies, and barren terrain. These results demonstrate how LULC dynamics vary widely along the CPEC route and emphasize how crucial it is to take local context and environmental considerations into account when developing land use planning and management methods. Concerns regarding possible effects on ecosystem services, biodiversity conservation, and water resource management in the Quetta region are raised by the reported reductions in water bodies and wetlands. To inform targeted actions and policy responses, more research is necessary into the factors that are driving these shifts, such as urban growth, agricultural intensification, and climate variability. The differences in changes to LULC between Quetta and the other CPEC-affected regions highlight the necessity of region-specific land use planning and management strategies that are adapted to the unique socioeconomic and environmental circumstances of each area. Developing integrated and sustainable land use strategies that strike a balance between social fairness, environmental conservation, and economic development requires the cooperation of stakeholders from the public and private sectors.

6. Future Direction And Scope Of The Research

The research on LULC changes along the Quetta to Gwadar China-Pakistan Economic Corridor (CPEC) route offers promising directions for future investigations:

- Extending the study's timeframe beyond the five-year period (2018 to 2022) will provide valuable insights into land cover trends over the entire CPEC project lifespan. Long-term monitoring enables understanding of critical transition periods, policy effectiveness, and future projections.

- Integrating climate change data and modelling can enhance our understanding of how climatic factors influence LULC changes. Assessing climate-related impacts on land cover dynamics will aid in developing climate-resilient strategies.

- Investigating land degradation processes and soil health along the CPEC route can identify vulnerable areas. Targeted land restoration and sustainable management strategies can be formulated to preserve ecosystem services.

- Utilizing research findings in land use planning will lead to more informed decision-making. Spatial simulations and land use scenarios can assess potential development impacts and support sustainable planning.

- Evaluating the ecosystem services provided by different land cover types will guide conservation efforts and sustainable development, considering services like water regulation and carbon sequestration.

- Integrating social and economic data can reveal the human dimension of LULC changes. Understanding development impacts on communities and livelihoods will promote inclusive policies.

- Exploring LULC changes at different scales (local to regional) will provide a comprehensive understanding of spatial variations. Targeted interventions can be designed accordingly.

7. Conclusion

This study conducted a thorough analysis of Land Use Land Cover (LULC) changes over the past five years (2018 to 2022). The overall classification accuracy showed remarkable improvement, reaching 87.4% in 2018 and an impressive 95.7% in 2022, highlighting the effectiveness of our approach for LULC change detection. The findings revealed significant declines in water bodies, wetlands, and barren land in Quetta, compared to Gwadar, Turbat, and Hoshab. Conversely, built-up areas and agricultural lands saw substantial growth along the study route during the same period. These results have crucial implications for policymakers and stakeholders, guiding them towards sustainable resource management and environmental conservation strategies.

Acknowledgement

The author also thanks China Study Centre, BUITEMS for providing logistics and survey supports for conducting and conceptualizing the research

The authors also thank Spatial Decision Support System Lab (SDSSL), BUITEMS under the National Center for GIS and Space Applications (NCGSA) and China Study Center, BUIEMS for their functional and technical support.

Additionally, the following information was supplied regarding data availability: The raw review data compiled for this article is available in the Supplemental File.

- https://code.earthengine.google.com/f8b9bbf2057b14d6c5c8921959 69d93f

- https://code.earthengine.google.com/4b141d8c7bd4f4ab7635da1adf 24158d

- https://code.earthengine.google.com/eb5a5cb343b53a3b87564e627 acddb91

- https://code.earthengine.google.com/949d4ee60742b8da3cff86df15d 2a87e

- https://https://code.earthengine.google.com/045ed26d970b7a8f218 8a25b84cae7f7

- https://code.earthengine.google.com/1e0259fd81e64a4393bd901cbe 9927f2

Author Contribution

Basma conducted field surveys, analyzed satellite imagery, and contributed to the methodology section. Shafi Ullah reviewed existing literature, assisted with data preprocessing, and drafted relevant sections. Raja Asif developed a land cover change detection algorithm and wrote the results and discussion. Lastly, Bakhtiar Kasi coordinated the project, contributed to the conclusion, and ensured overall coherence.

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