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Research Paper

Development of a map for land use and land cover classification of the Northern Border Region using remote sensing and GIS

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ABSTRACT

The land use and land cover study (LULC) play an essential role in regional socio-economic development and natural resource management to develop sustainable development in vegetation changes, water quantity and quality, land resources, and coastal management. This study uses remote sensing data to investigate LULC in the Northern Border Region (NBR) in the Kingdom of Saudi Arabia. The purpose of this study is to obtain a better understanding of the patterns and drivers of changes in LULC in the NBR over the past three decades. Remote sensing data from Landsat imagery between 1990 and 2022 were used to classify LULC types, and a time series analysis was performed using Landsat imagery to detect changes over time. The classification finds four main classes: bare land, built-up area, rocks, and vegetation. The results indicate a significant increase in urban development. The outcomes revealed that most urbanization occurred in the outskirts of the cities, where previously there were bare soil lands. The main drivers of urbanization were population growth and economic development. These findings have important implications for city planning, the management of green spaces, and the sustainable development of cities. Maximum Likelihood classifier was used to perform the classification. The accuracy assessment demonstrated satisfactory results, with an overall accuracy of 92.6%. The study paves the way for further monitoring LULC changes in the NBR geographic location. The technique used was adequate to address the objectives of this study.

1. Introduction

LULC is a source of information for countries to make appropriate decisions based on remote sensing (RS) data. This knowledge and detection of land change are considered essential factors for planning land conservation, management, and development. Understanding the dynamics of environmental change to ensure sustainable development and formulate policies for the optimal future use of these lands. LULC classification is an important technique to assess the relationship between the environment and human activities (Singh et al., 2021). It studies how different land uses are distributed in a particular area. This type of analysis is widely used in a variety of applications, including conservation planning, urban planning, and disaster management. LULC has become increasingly important as the human population grows and the planet's resources are stretched to their limits. LULC classification involves identifying and categorizing different types of land cover within an area, collecting data through field or RS surveys and other methods such as satellite imagery. The data can then be compiled and organized into a decision-making hierarchy. The main objective of the classification system is to accurately identify the type of land cover present in a given area. The most widely used method for LULC classification is traditional visual interpretation. It involves passing a trained expert over the land area in question and requesting detailed reports on the present land cover. The specialist is asked to provide a subjective assessment of the land, such as its vegetation cover or water bodies. Such a visual interpretation helps provide a detailed understanding of a given area but can be unreliable and unsuitable for large-scale LULC analyses. An alternative to visual interpretation is object-based image analysis (OBIA). This method involves segmenting an image into distinct objects based on their physical characteristics, such as shape and texture, and assigning a LULC class to each object. This approach is helpful for large-scale LULC classification, as it can process large amounts of image data quickly and accurately. OBIA is more reliable and requires less user input than traditional visual interpretation. The use of machine learning and artificial intelligence is gaining attention as a new method for LULC classification. This approach involves training a computer model to

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identify LULC classes from satellite images by learning from labelled training data. It can be done using various models, such as convolutional neural networks (Balarabe and Jordanov, 2021), deep belief networks (Lv et al., 2015; Vignesh and Thyagharajan, 2019), support vector machines (Hamad, 2020; Kadavi and Lee, 2018; Rezaei Moghaddam et al., 2015; Aslami et al., 2015), and others. Machine learning has the advantage of quickly processing massive amounts of data and providing more accurate results than traditional LULC classification methods.

This research study is significant because the growing population and the increasing socio-economic had created pressure on LULC, which led to unplanned and uncontrolled changes. The Northern Border Region is a critical ecological and economic zone that encompasses a variety of land uses and covers, including urban areas, agricultural lands that has not been used, and natural ecosystems. However, the region is undergoing rapid and extensive land-use changes, resulting in significant impacts on local communities, natural resources, and the environment. Therefore, it is essential to develop accurate and efficient tools to monitor and manage land use and land cover changes in the region. Remote sensing and GIS technologies offer a powerful means to quantify and analyze LULC changes, but their application requires a specific method tailored to the unique characteristics of the study site. Our study aimed to develop a map for land use and land cover classification of the Northern Border Region using remote sensing and GIS, which can provide a reliable and efficient tool to monitor and manage land use and land cover changes in the region. The study's results can contribute to the development of effective land management policies and practices, promote sustainable land use and resource conservation, and provide critical information for urban planning, agricultural management, and biodiversity conservation. The KSA plays a crucial role in global efforts to preserve the future of the Earth, as it launched the Green Saudi Initiative to renew its belief in a sustainable future for all. From this point of view, there was a need to study the environment and topography of the Kingdom from several points of view to delineate the maps of LULC. Information and data are needed to help decision-makers detect the change in the LULC of the NBR and understand the dynamics of environmental change to ensure sustainable development and formulate policies for the optimal future use of these lands. There are no previous studies covering the LULC of the Northern Border region. The generated and processed maps that will result from this study will be significant for the future planning of the NBR. In this study, RS techniques will be used to map the land use and cover of NBR, one of the most critical regions of the Kingdom in terms of environmental diversity, in addition to the presence of many essential minerals. Decision-makers can use the results of this study to manage natural resources in the region, help in socio-economic development, plan the appropriate use of land (agriculture, construction, and urban expansion), and know the size and type of vegetation in the northern border area. The maps from this study will help find suitable places for mining essential minerals in the northern border region.

The rest of this paper is structured as follows: Section 2 provides background information on the topic, followed by a review of relevant literature in Section 3. Section 4 describes the research design, including the deadest materials and procedures. Section 5 presents the study findings, including the statistical analyses and data classes. Section 6 presents the Challenges and Limitations, followed by the conclusion to summarize the main findings and their implications.

2. Background

LULC classification is a fundamental tool for understanding the spatial distribution of land features and their associated characteristics. Accurate LULC classification is essential for various land management, natural resource management, and urban planning applications. Due to the rapid advancement of RS technology, high-resolution images are now available with a wide range of spectral and spatial resolutions, allowing for accurate and timely land cover classification. However, due to the complexity of land features, the classification of LULC remains challenging. A key factor affecting the accuracy of LULC classification is the selection of features for classification. There are many classification methods. The following sections briefly describe the classification and feature selection methods.

The three main methods for classifying LULC objects using RS and GIS are satellite imagery, spectral analysis, and digital terrain analysis. First, satellite imagery involves using satellites to acquire images of land surfaces from different angles. These images are then processed and analyzed to identify and classify LULC objects. The data collected can include details such as elevation, vegetation, and soil type. Second, spectral analysis is used to identify and classify LULC objects using electromagnetic radiation (EMR) emitted from these objects. This technique uses different wavelengths of EMR, such as infrared, visible light, and thermal imaging, to detect and characterize different LULC objects. Third, digital terrain analysis involves using computer algorithms and GIS software to analyze and classify LULC objects. This technique is used to create detailed contour maps and 3D models of terrain in order to classify and identify LULC objects accurately.

3. Literature review

Various studies have been conducted to classify and update LULC information in different regions using RS and GIS technology with varying levels of success (Sang et al., 2021; Bhattacharya et al., 2021; Dibs et al., 2020; Kaya and Görgün, 2020; Saddique et al., 2020; Ghayour et al., 2021). Abdallah et al. (2019) used three cloud-free Landsat MSS, ETM +, and OLI images to classify LULC classes and land cover changes in Jizan Dam, Saudi Arabia. The study successfully identified five classes (Vegetated land, Urban area, Bare area (sands), Bare area (rocks), and water bodies) with an overall accuracy of 86.67%. As part of their classification of Makkah and Al-Taif in Saudi Arabian Desert Cities, Alqurashi and Kumar (2014) incorporated maximum likelihood and object-orientated classification methods. Among the five identified classes vegetation, urban landscape, barren land, sand, and rocky terrain. There was an average accuracy of 88.9 percent for maximum likelihood classification for 1986, 1990, 2000, and 2013, while 92.5 percent for object-oriented classification for those years. According to the findings, urban areas grew by around 174% in Makkah and 113% in Al-Taif. As a result of changing average precipitation in this environment, the distribution of vegetation cover over the study area varies from year to year (Alqurashi and Kumar, 2014). Mahmoud and Alazba (2016) estimated the spatial and temporal distribution of actual evapotranspiration (AET) in KSA's western and southern regions from 1992 to 2014 using the SEBAL model and field observations. Salih (2018) applied different image preprocessing techniques and a well-known and widely used classification method (i.e., Maximum Likelihood classifier). Also, Khwarahm (2021) Maximum Likelihood classifier to model and analyze LULCC trends in the Sulaimani region in Iraq. Khwarahm et al.(2021) presents a study on predicting and mapping land cover/land use changes in Erbil, Iraq using a CA-Markov synergy model. Landsat-7 data was used in this study to classify and map land cover types and attributes in Al-Ahsaa Oasis, Eastern Region, Saudi Arabia. The Landsat images of AlKhobar, Saudi Arabia, have been used by Rahman (2016) to quantify land use/cover changes and urban sprawl over 23 years. It uses ISODATA classification methods to classify Landsat TM, ETM+, and OLI data. The rate of urban development increased from 17% between 1990 and 2001 to 43.51% between 2001 and 2013. Furthermore, vegetation increased by 110 percent between 1990 and 2001 and 52 percent between 2001 and 2013. Several studies also used RS and GIS for LULC. Alawamy et al. (2020) used time-series Landsat data from 1985 to 2017 to detect and analyze LULC changes in Al-Jabal Al-Akhdar, Libya. Wijitkosum (2016) illustrated the impact of land use and spatial changes on the risk of desertification in degraded areas in Thailand. Research studies have shown that using RS and GIS technologies provides efficient and accurate ways to detect and classify LULC. Furthermore, RS data-driven classification technology is increasingly used for LULC mapping to obtain accurate and timely data.

4. Materials and methods

The workflow diagram of this study can be illustrated in Fig. 1.

4.1. Study area

The study area is in Saudi Arabia's Northern Border Region (NBR), along the borders with Iraq and Jordan. It consists of several towns, villages, land, and semi-arid areas. The elevation of the area is 536 m above sea level. The GPS coordinates of NBR are 30.975 and 41.038, and its longitude is 41.016666. 30° 59′ 0.0024″ N and 41° 0′ 59.9976″ E (https://en.wikipedia.org/wiki/Arar,_Saudi_Arabia). Its population is 395,000 (the year 2014 census). It is recognized for its fertile grazing plains. The Saudi Arabian Highway 85 passes through NBR, a significant supply stop connecting Iraq and Saudi Arabia. Fig. 2 shows the location of NBR on the map.

4.2. Dataset collection

The dataset consists of RS imageries of NBR's maps from 1990 to 2022. It was extracted using Landsat 5 and Landsat 8 from various satellite images repository like Google Earth Pro, the United States

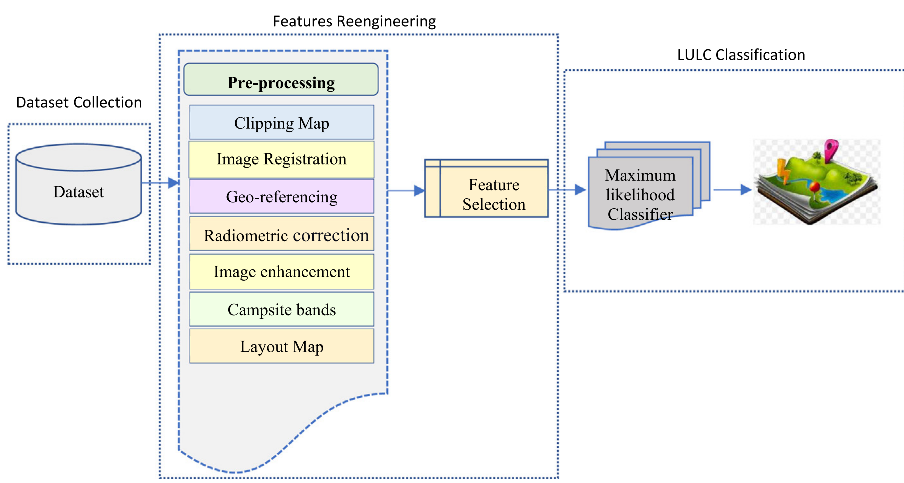

Fig. 1. Workflow Diagram.

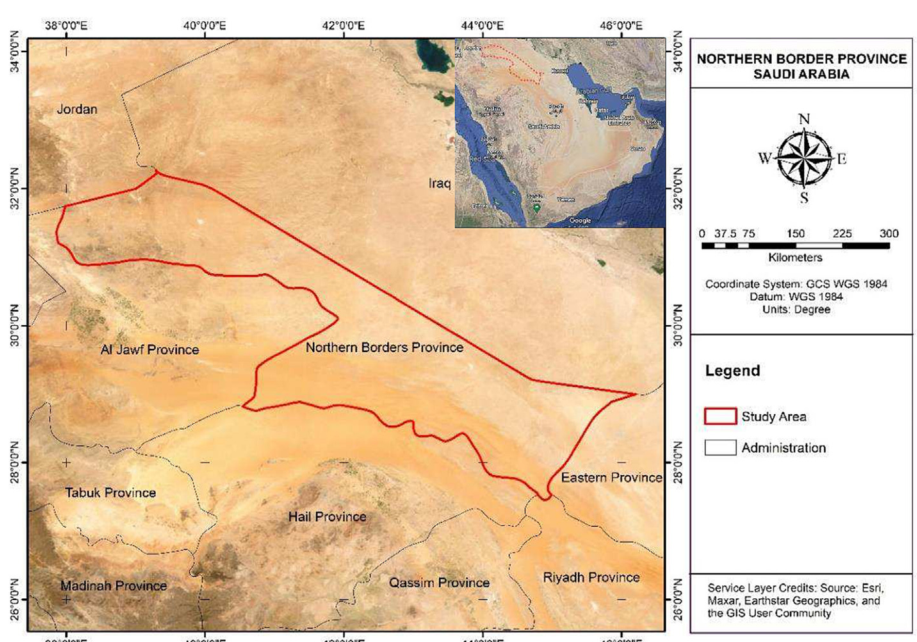

Fig. 2. Study Area NBP in Saudi Arabia.

Table 1
Sensor and Date/time of the scene acquisition from Landsat 5 Thematic Mapper (TM) and Landsat 8 (OLI).

Path	Row	Landsat 5 (TM)					Landsat 8 (OLI)		
168	39	12/18/1990	11/14/1995	12/29/2000	11/25/2005	12/9/2010	12/7/2015	12/20/2020	12/18/2022
168	40	12/18/1990	11/14/1995	12/29/2000	11/25/2005	11/23/2010	12/7/2015	12/20/2020	12/18/2022
168	41	12/18/1990	11/14/1995	12/29/2000	11/25/2005	11/23/2010	12/7/2015	11/18/2020	12/18/2022
169	39	12/9/1990	12/7/1995	11/2/2000	6/25/2005	11/30/2010	11/28/2015	12/11/2020	12/25/2022
169	40	12/9/1990	12/7/1995	12/20/2000	10/15/2005	11/30/2010	11/28/2015	12/11/2020	12/25/2022

Geological Survey (USGS)[1] and (diva)[2] website. These images were clear of cloud cover. Table 1. Shows the Sensor and Date/time of the scene acquisition from Landsat 5 Thematic Mapper (TM) and Landsat 8 (OLI).

4.3. Pre-processing

Data pre-processing is an essential part of LULC classification, as it affects the accuracy of the resulting classification outputs. Data pre-processing is a method used prior to LULC classification to optimize the accuracy of the classification results. It helps the data to be improved to provide better results. Data pre-processing encompasses various stages, such as radiometric corrections, data enhancement, and spatial filtering, which are essential for obtaining more accurate classifications. Radiometric corrections are performed to compensate for sensor gain and offset effects, which can adversely affect the LULC classification results. The primary radiometric corrections used in LULC classification are signal-to-noise ratio adjustment and histogram equalization. The signal-to-noise ratio adjustment minimizes the variation so that the output image has a more even signal distribution. Histogram equalization compensates for the non-uniform luminance distribution in regions with varying illumination intensity by redistributing the pixel values across the entire dataset.

It is crucial to pre-process the RS data to correct the radiometric and geometric inaccuracy that occurs during acquisition, scanning, and transmission. The pre-processing steps include clipping maps, image registration, geo-referencing, radiometric correction, image enhancement, campsite bands, and layout maps. These steps improve image quality and remove noise sources, providing a more reliable dataset. The steps are described as follows: i) Clipping maps are used to cut out specific regions of interest from the original images. It is done by cutting out unneeded background information, allowing images to be analyzed more precisely. ii) Image registration is a process of aligning images of different areas together, allowing similar features to be compared. It can also match the coordinate systems of two images taken at the exact location (Ramdani et al., 2021). The image registration is done through SOMINFO, which must be installed in the plugin management from the plugin's menu inside QGIS. iii) Geo-referencing is a process to assign locations to images, allowing a computer to identify the location of various land cover objects. In contrast, geometric correction entails moving a pixel's location using coordinates without altering its luminous reflectance and recalculating its radian value using resampling. Then, geometric rectification is done using ArcMap with the projection WGS 1984 UTM 37 N by placing the pixels in their accurate planimetric (x, y) map coordinates. iv) The radiometric correction is then used to normalize the look of the image, making it easier to identify land cover classes. To increase the accuracy of the brightness value magnitudes, radiometric correction of RS photos mainly entails the processing of digital images. The primary objective of radiometric correction is to reduce the impact of inaccuracies or inconsistencies in the image's brightness values (Kuemmerle et al., 2013). Geometric and radiometric corrections are made in this step. The accuracy of the product is improved by radiometric and geometric adjustments, which are both highly helpful in removing impacts brought on by varying correction orders. To prevent radiometric errors or distortions, radiometric calibration and atmospheric correction recalculation of the pixel's radiance is carried out. Geometric correction involves employing registration to eliminate geometric distortion, corrections of local incident angle with toposheet, and knowledge of the geodetic coordinates of some related ground sites (Kuemmerle et al., 2013; Alshari and Gawali, 2021; Verburg et al., 2011; Shi et al., 2020; Alshari and Gawali, 2021). v) Image enhancement techniques used for noise removal and enhanced features in the images retrieved from Landsat 5 and Landsat 8, making them easier to identify. These operations seek to improve satellite images for improved classification and repair the degraded image to depict the original scene (Alqadhi et al., 2021) accurately. Because these procedures are carried out before the data is used for a specific purpose, correcting shortcomings and eliminating faults from the data are referred to as pre-processing (Ramdani et al., 2021). Due to atmospheric effects and the sensing system's limits, the likely range of pixel values may not be fully utilized while acquiring data while creating RS imagery. As a result, acquired data may be of low quality, such as having little contrast, a dark overlay, or much radiometric noise (Linda Theres and Selvakumar, 2022). Therefore, it refers to the functions performed regularly to enhance the geometric and radiometric quality of the photographs. vi) Composite Band Images are created by combining multiple bands of information from environmental spectrum sensors. Each information band contains data from several spectral regions within the larger electromagnetic spectrum, such as near-infrared, visible, and shortwave infrared. Each band collects information about different aspects of the environment, such as reflectance and vegetation indices. When multiple information bands are combined in a composite band image, a greater understanding of the characteristics of the environment can be appreciated. These composite images are then used to identify and map LULC features. vii) Layout Maps are used to map the boundaries of the land cover classes, providing an outline of the land cover types within the image. The layout process maps the information obtained from composite band images into limited patterns corresponding to LULC features. For example, areas of high near-infrared reflectance may be classified as evergreen forests, while areas of low visible and near-infrared reflectance may be classified as agricultural land. Layout maps also allow for

Table 2
Classes' Description.

No.	Class	Description
1.	Bare land	Bare soil and land do not contain the population of people like the desert.
2.	Built-up Area	The built area can be a large or small building.
3.	Rocks	Mountains or bare rocks
4.	Vegetation	Space containing sparse grasslands.

[1] https://www.usgs.gov/.
[2] https://www.diva-gis.org/.

Table 3
LULC Changes in NBR between 1990 and 2022.

Classes	Years/Area (km^2)							
	1990	1995	2000	2005	2010	2015	2020	2022
Bare land	114,053	113,272	113,174	113,080	113,325	112,660	112,603	112,977
Built-up Area	21	24	31	57	77	105	122	133
Rocks	3417	4193	4277	4346	4084	4714	4751	4359
Vegetation	1	3	10	9	11	13	16	23
Total	117,492	117,492	117,492	117,492	117,492	117,492	117,492	117,492

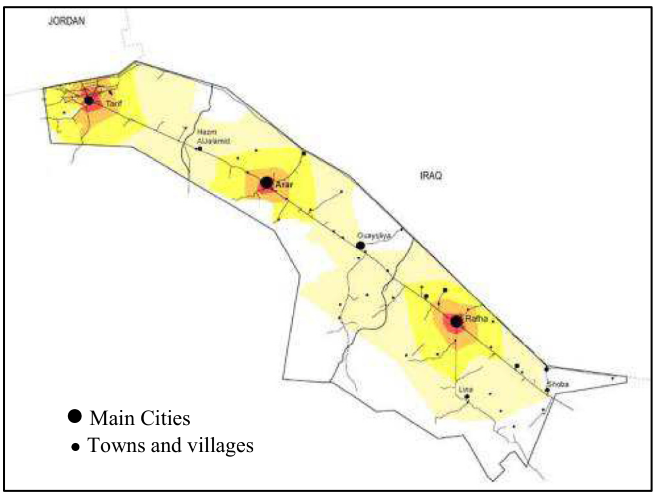

Fig. 3. The built-up area in NBR.

images to be compared, helping to identify detailed changes in the LULC features over time. Figures 13 and 14 show the layout map for 2012 and 2022, respectively.

5. Results & discussion

To classify the re-travel segmented images. We used maximum likelihood classification (MLC) to classify images based on specific features. Eq. (1) is used as a discriminant function for each pixel in the image. The classified images are used to analyze and predict changes over time.

$$g_i(x) = 1n\ p(w_i\ ) - 1/2\ 1n\ |\sum_i| - 1/2(x - m_i)^T \sum_i^1 (x - m_i) \qquad (1)$$

Where: $\boldsymbol{x}$ *=* $\boldsymbol{n}$*-dimensional data (where n is the number of bands);* $\boldsymbol{i}$ *= class;* $\boldsymbol{p(\omega_i)}$ *= probability that class* $\boldsymbol{\omega_i}$ *occurs in the image and is assumed the same for all classes;* $\boldsymbol{|\Sigma_i|}$ *= determinant of the covariance matrix of the data in class* $\boldsymbol{\omega_i}$*;* $\boldsymbol{\Sigma_i^{-1}}$ *= its inverse matrix;* $\boldsymbol{m_i}$ *= mean vector.*

This study recognized four classes: bare land, Built-up area, rocks, and vegetation. The classes' details are described in Table 2, Table 3, and Fig. 4.

All LULC classes in the northern border region from year to year have changed. The built-up area increased from 1990 with 21 km^2 wide to 2022 with 132 km^2 wide area. Vegetation also increased from 1990 at 1 km^2 wide to 2022 at 23 km^2 wide. Changes that happened to Rocks and Bare Land are not increased or decreased constantly. The possibility that made it happen is because the satellite captured rocks covered by sand or vice versa.

The built-up area class experienced the most significant change in NBR. The results showed that urban areas increased by approximately 628% between 1990 and 2022. It is a predictable situation because the increment of human activity, such as construction and urban development, will continue to drive growth. The built-up area in NBR is shown in Fig. 3. Due to the changing average precipitation in this environment, the distribution of vegetation cover over the study area varied slightly from year to year. The vegetation is limited to sparse grassland and public parks. There are no patterns to indicate any crops. There is no constant increase or decrease in the changes to the Rocks and Bare Land classes. It could have happened because the satellite captured rocks covered by sand or vice versa. Table 4 shows the LULC change trends of the study area in 1990 compared to 2022.

Our work on developing a map for land use and land cover classification of the Northern Border Region using remote sensing and GIS is an important contribution to the field of environmental monitoring and natural resource management. Our approach utilizes advanced remote sensing and GIS techniques to achieve a higher accuracy of land use and land cover classification, which is essential for sustainable land management, natural resource conservation, and environmental monitoring.

Our approach has several potential applications in different fields, such as urban planning, agricultural management, and biodiversity conservation. In urban planning, accurate land use and land cover classification maps can be used to identify areas suitable for development, estimate population density, and monitor changes in the built environment. In agricultural management, such maps can be used to identify land use patterns and estimate crop yields, which can inform decisions on land use planning and resource allocation. In biodiversity conservation, our approach can be used to identify areas with high ecological value and potential threats to biodiversity, which can inform conservation strategies.

This work also contributes to the ongoing efforts to monitor and understand the land use and land cover changes in the Northern Border Region. Such information is essential for policymakers, land managers, and researchers to develop effective strategies to promote sustainable land use practices and natural resource conservation.

6. Accuracy assessment

The confusion matrix of ground truth data and the Kappa coefficient were used to assess accuracy. Ground-truth data were gathered from fieldwork carried out in NBR. A confusion matrix is a popular tool for evaluating LULC classification techniques' accuracy (Rizvon and Jayakumar, 2022; Tan et al., 2021). It can be used alone or with other accuracy assessment techniques to assess the quality of the classification. A confusion matrix is a powerful tool for assessing accuracy in LULC classification (Alshari et al., 2022). It is used to express the performance of the classification and calculate false positives, false negatives, true positives, and true negatives.

The accuracy assessment with the confusion matrix often offers more profound insights into the results of the classification pro-

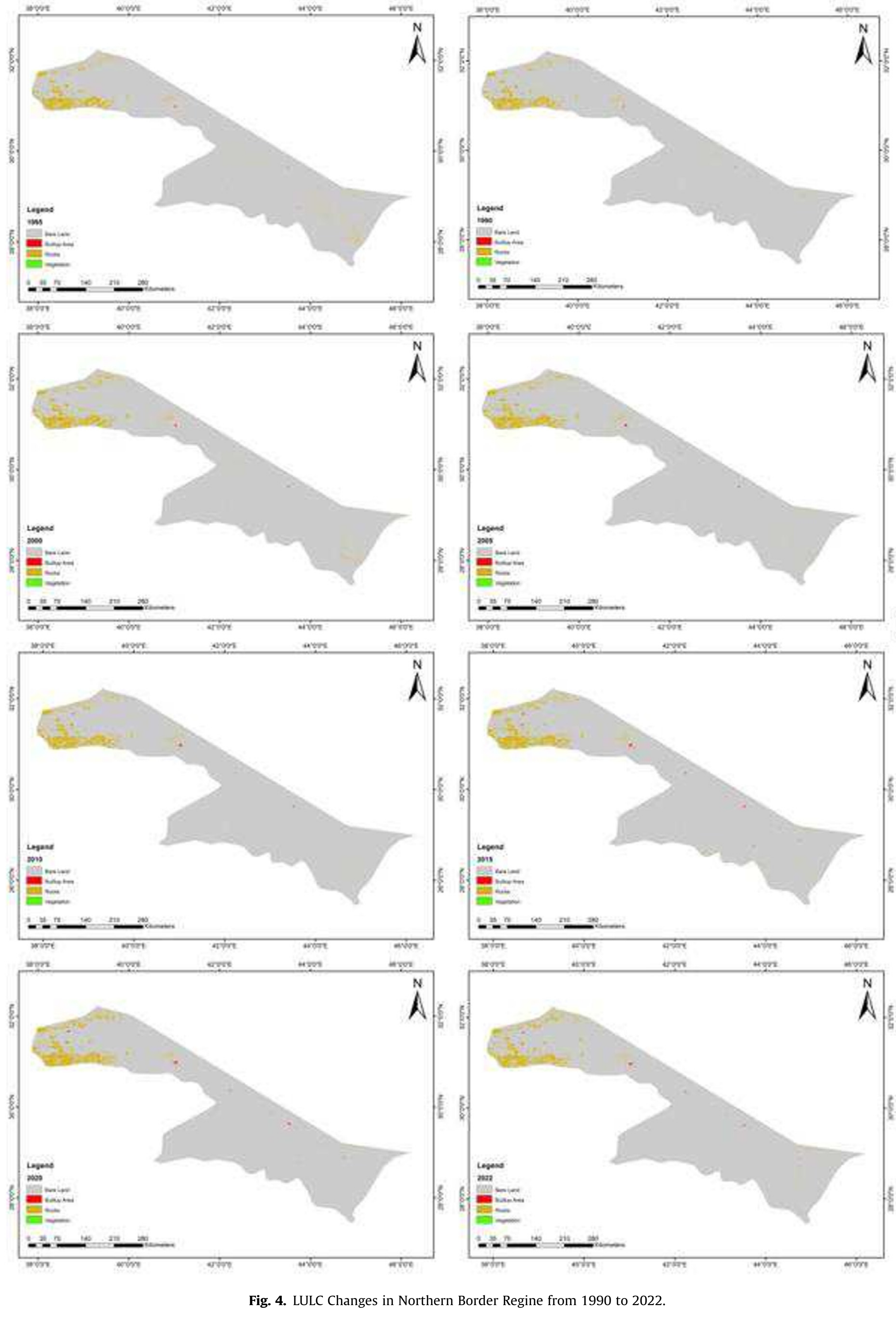

Fig. 4. LULC Changes in Northern Border Regine from 1990 to 2022.

Table 4
LULC change trends of the study area.

Classes	1990		2022		LULC change (1990–2022) %
	Area (km2)	%	Area (km^2)	%	
Bare Land	114,053	97.07	112,977	96.16	0.92
Builtup Area	21	0.02	133	0.11	−0.10
Rocks	3417	2.91	4359	3.71	−0.80
Vegetation	1	0.00	23	0.02	−0.02
Total	117,492	100	117,492	100	

Table 5
Confusion matrix in 1990.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	18	0	2	0	20	90
2	Built-up Area	0	17	3	0	20	85
3	Rocks	0	0	20	0	20	100
4	Vegetation	0	0	0	20	20	100
Total		18	17	25	20	Overall	94
Producer Acc. (%)		100	100	80	100	Acc. (%)	

Table 6
Confusion matrix in 1995.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	19	0	1	0	20	95
2	Built-up Area	0	16	1	3	20	80
3	Rocks	1	0	17	2	20	85
4	Vegetation	0	2	2	16	20	80
Total		20	18	21	21	Overall	85
Producer Acc. (%)		95	89	81	76	Acc. (%)	

Table 7
Confusion Matrix in 2000.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	20	0	0	0	20	100
2	Built-up Area	1	17	0	2	20	85
3	Rocks	0	0	20	0	20	100
4	Vegetation	0	0	0	20	20	100
Total		21	17	20	22	Overall	96
Producer Acc. (%)		95	100	100	91	Acc. (%)	

Table 8
Confusion matrix in 2005.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	20	0	0	0	20	100
2	Built-up Area	0	19	1	0	20	95
3	Rocks	1	0	17	2	20	85
4	Vegetation	0	0	0	20	20	100
Total		21	19	18	22	Overall	95
Producer Acc. (%)		95	100	94	91	Acc. (%)	

cess, making it a valuable tool for LULC classification tasks. Additionally, it can be used to compare the performance of different techniques or assess the accuracy of a particular technique concerning a reference classifier. The confusion matrix results are described in Tables 5–12. The kappa coefficient is calculated as follows:

$$k = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)} \tag{2}$$

Where: $\boldsymbol{N}$ is the total number of classified values compared to truth values; $\boldsymbol{i}$ is the class number; $\boldsymbol{m_{i,i}}$ is the number of values belonging to the truth class $\boldsymbol{i}$ that have also been classified as class

Table 9
Confusion Matrix in 2010.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	20	0	0	0	20	100
2	Built-up Area	1	17	0	2	20	85
3	Rocks	2	0	18	0	20	90
4	Vegetation	0	1	0	19	20	95
Total		23	18	18	21	Overall	93
Producer Acc. (%)		87	94	100	90	Acc. (%)	

Table 10
Confusion matrix in 2015.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	20	0	0	0	20	100
2	Built-up Area	0	19	1	0	20	95
3	Rocks	1	0	18	1	20	90
4	Vegetation	2	0	1	17	20	85
Total		23	19	20	18	Overall	93
Producer Acc. (%)		87	100	90	94	Acc. (%)	

Table 11
Confusion Matrix in 2020.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	20	0	0	0	20	100
2	Built-up Area	0	17	0	3	20	85
3	Rocks	4	0	16	0	20	80
4	Vegetation	0	0	0	20	20	100
Total		24	17	16	23	Overall	91
Producer Acc. (%)		83	100	100	87	Acc. (%)	

Table 12
Confusion matrix in 2022.

ID	Classes	Classification results				Total	User Acc. (%)
		1	2	3	4		
1	Bare land	19	0	0	1	20	95
2	Built-up Area	0	19	1	0	20	95
3	Rocks	2	0	17	1	20	85
4	Vegetation	0	0	0	20	20	100
Total		21	19	18	22	Overall	94
Producer Acc. (%)		90	100	94	91	Acc. (%)	

Table 13
Overall accuracy and Kappa coefficient.

Year	Accuracy	Kappa Coefficient
1990	94%	0.92%
1995	85%	0.80%
2000	96%	0.95%
2005	95%	0.93%
2010	93%	0.90%
2015	93%	0.90%
2020	91%	0.88%
2022	94%	0.92%
Overall accuracy	92.6%	90%

$\boldsymbol{i}$; $\boldsymbol{G_i}$ is the total number of truth values belonging to class $\boldsymbol{i}$; $\boldsymbol{C_i}$ is the total number of predicted values belonging to class $\boldsymbol{i}$.

Table 13 shows the overall accuracy and Kappa coefficient. The Kappa coefficient values in each year are in substantial and perfect agreement, with a range of 80% to 95%. The overall precision is 92.6%, indicating that the classification has a reasonable accuracy rate.

7. Challenges and limitations

While the current developments in RS and GIS LULC classification are promising, there are still limitations and challenges. First, the accuracy of collected data can vary depending on the type of equipment used and the environment in which the data was collected. Due to the nature of the classification process and the challenges of detecting small-scale land-use changes, there is a need to improve the accuracy of the classification process. It can be achieved by deploying more sophisticated RS platforms and algorithms. For example, one future direction is combining many machine learning and deep learning algorithms to improve the accuracy of LULC classification. Furthermore, multimodal data fusion can be applied to improve the quality of classification algorithms, and pixel-based classification techniques can be used to analyze subtle changes in LULC at a fine scale. Second, data acquisition and processing costs can be high, making it difficult for smaller organizations or researchers to obtain the resources needed to carry out the analysis. Finally, the resolution of the imagery can be limited, making it difficult to detect small LULC objects accurately.

8. Conclusions

This study aimed to investigate LULC changes in NBR over the past three decades to understand the patterns and drivers of LULC. The study utilized RS data from Landsat imagery between 1990 and 2022 and conducted a time-series analysis to detect changes over time. Four classes were identified: bare land, built-up area, rocks, and vegetation. The results showed that there had been a significant increase in urbanization and a decrease in bare soil and green spaces during this period. Most of the urbanization occurred in the outskirts of the cities, where previously there was bare soil. The main driver of urbanization was population growth and economic development. The finding showed how human factors and processes have greatly affected the shapes and disappearance of many forms of the Earth's surface between 1990 and 2022. The study provides a reliable baseline for monitoring changes in the LULC of the study area and can be used as a starting point in other studies that involve a change in land cover in the NBR. The outcomes show that the classification scheme accurately mapped the NBR's LULC classes, with an overall accuracy of 92.6% and a Kappa coefficient of 0.90. This study demonstrated the usefulness of remote sensing and GIS techniques for mapping and monitoring LULC change dynamics in the Northern Border Region over an extended period of time. However, the limitations and challenges identified in this study also highlight the need for more advanced techniques to predict LULC change dynamics in the future. Therefore, it is recommended that future studies in the region should explore more advanced machine learning and artificial intelligence techniques, such as deep learning, to improve the accuracy and efficiency of LULC classification and prediction. In addition, incorporating ancillary data sources, such as socioeconomic and environmental variables, could provide a more comprehensive understanding of the driving factors of LULC change in the region. Such studies would not only advance our knowledge of LULC dynamics in the region but also inform effective land management and planning strategies for sustainable development.

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.

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