





# Quantifying the Impact of Chashma Right Bank Irrigation Project on the Land use Dynamics and Cropping Pattern of Arid Region, Pakistan

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**Citation** | Marwat. F, Rahman. A, Manglore. U, Naz. T, Khan. Z, Zahid. B, Khan. A, Dilbar. S, "Quantifying the Impact of Chashma Right Bank Irrigation Project on the Land use Dynamics and Cropping Pattern of Arid Region, Pakistan", IJIST, Special Issue pp 125-138, June 2024 **Received** | May 25, 2024; **Revised** | May 31, 2024; **Accepted** | June 03, 2024; **Published** | June 08, 2024.

his research evaluates the impact of the Chashma Right Bank Irrigation Project (CRBIP) on land use dynamics and cropping patterns in an arid region of Pakistan. Initiated in 1984 and completed in three stages by 2003, the CRBIP encompasses 250,000 acres across Khyber Pakhtunkhwa and Punjab. The primary goal of the CRBIP was to enhance agricultural productivity and create employment opportunities. To analyze the geographical and temporal changes in land use dynamics, this study employed remote sensing and GIS techniques. Data were collected from both primary and secondary sources, with satellite images obtained from the years 1991 to 2021. Landsat 5 (TM) images for 1991 and 2011, Landsat 7 (Enhanced Thematic Mapper) for 2001, and Landsat 8 (Operational Land Imager/Thermal Infrared Sensor) for 2021 were sourced from the USGS Earth Explorer. Additionally, crop production data were gathered from the statistics wing of the agriculture department. The results indicate notable changes over the past three decades: vegetation cover increased by 8.8%, built-up areas expanded by 15%, barren land decreased by 24%, and water bodies saw a slight reduction of 0.14%. The study also highlights significant spatial and temporal variations in vegetation cover. Following the implementation of the CRBIP, there has been a gradual increase in irrigated areas. The analysis reveals substantial improvements in the acreage of both Kharif and Rabi crops as a result of the CRBIP. These findings offer valuable insights for land-use planners, researchers, policymakers, and municipal authorities, contributing to informed decision-making and strategic planning in the region.

Keywords: CRBIP. GIS. Spatio-Temporal. Land Use. Crop Production.





### Introduction:

As the global population continues to rise, the construction of dams, irrigation projects, and other infrastructure will remain crucial, particularly in developing countries [1]. Agriculture faces the pressing challenge of increasing food production amid dwindling water resources. Water productivity, which measures the value or benefit derived from water use, plays a vital role in managing resources effectively, especially in arid and semi-arid regions. Irrigation is essential for agricultural development, acting as the backbone of sustainable agriculture. It not only prevents starvation and saves lives but also boosts a country's material wealth [2]. By applying water to land, irrigation maximizes economic output and enhances crop production, though it often requires more water than natural rainfall [3]. Despite water being one of the planet's most abundant resources [4], only 1% is readily available for human use [5]. Between 1955 and 1990, per capita fresh water availability in many Asian countries decreased by 40-60% [6].

Effective land and irrigation management are crucial for improving water use efficiency and agricultural production [7]. Enhancing water productivity involves either achieving the same yield with less water or increasing crop yields with the same amount of water. Climatic changes affecting crop production can significantly influence both regional and global food supplies. Irrigation, the process of artificially supplying water to crops, is becoming increasingly important [8]. Innovations in canal irrigation are being adopted worldwide to improve water delivery efficiency and operational flexibility [9]. In Asia, irrigation plays a key role in boosting crop production. In Pakistan, it contributes significantly to food security, supporting over 70% of agricultural needs in China and more than 50% in India and Indonesia [10]. Canal irrigation has a profound impact on land use and land cover globally, with irrigated agriculture being critical to the economic prosperity of many nations [11]. Managing water resources in arid and semi-arid regions is particularly challenging, especially where rainfall is the primary water source [12].

Pakistan, with its extensive irrigation system, exemplifies the importance of canal irrigation [13]. Covering around 79.6 million hectares, with approximately 23 million hectares suitable for agriculture [14], Pakistan boasts one of the world's largest gravity-flow irrigation networks. This network includes three major reservoirs (Tarbela, Mangla, and Chashma), 19 barrages, 12 inter-river connection canals, two syphons, 45 main canal commands, and around 107,000 outlets. Annually, approximately 130 billion cubic meters of river water are diverted through canal irrigation systems [16]. However, water scarcity remains a significant challenge in arid regions due to low precipitation and high evapotranspiration [17].

In Tehsil D.I. Khan, water is a crucial resource with substantial potential for development, yet the sector has seen limited progress [18]. The region's arid to semi-arid climate limits crop yields, with rain-fed farming (barani) prevailing, while irrigation has the potential to convert wasteland into productive agricultural areas, contributing to self-sufficiency [19]. Analysis of isohyet lines indicates that annual rainfall decreases from north to south in the study area [20]. The Chashma Right Bank Canal Irrigation Project (CRBCIP), initiated in 1984, is one of Pakistan's largest projects aimed at transforming arid areas into productive farmland. In Tehsil D.I. Khan, CRBCIP ensures a consistent water supply throughout the year, leading to significant changes in land use and cover. This study aims to explore the spatio-temporal impact of the Chashma Right Bank Canal on land use dynamics, as depicted in the accompanying flow chart.

Flow Chart: Stages of Chashma Right Bank Canal Irrigation Project





### **Objectives:**

- To assess and quantify spatio-temporal land use land cover changes from 1991, 2001, 2011, and 2021 in the study area.
- To determine the impact of Chashma Right Bank Canal on LULC change and crop production.

### Novelty Statement:

The title of the current study focuses on the novel idea of examining land use and land cover (LULC) changes caused by the Chashma Right Bank Canal (CRBC). The major objective of this research is to determine the impact of the CRBC on the land use and land cover dynamics in Tehsil D.I. Khan, Khyber Pakhtunkhwa, due to the significant changes in agricultural land resulting from improved water availability.

### Materials and Methods:

### The Study Area:

The study area includes the southeastern fringe of Tehsil D.I. Khan. Tehsil D.I. Khan is situated between 31°18'22" to 32°26'07" North latitude and 70°31'08" to 71°08'29" East longitude (Figure 1). It is bordered to the north by Tank and Lakki Marwat, to the east by Bhakkar and Mianwali districts of Punjab province, to the south by District Dera Ghazi Khan, and to the west by Tehsil Kulachi and Tehsil Daraban.

The elevation in the study area increases from 2,460 feet in the north to 4,526 feet in the south. The climate features short, cold winters and long, warm summers, with June being the hottest month, reaching temperatures of up to 40°C. The average annual rainfall is approximately 280 mm [18]. Tehsil D.I. Khan covers an area of 3,394.4 square kilometers, with a total population of 725,499 and a population density of 213 people per square kilometer [21]. Before the CRBC was constructed, key crops in the area included gram, wheat, millet, and corn. However, the advent of the CRBC has led to a shift towards water-intensive cash crops such as sugarcane, rice, cotton, and pulses.

### Data Types and Management:

- The initial step involved acquiring satellite imagery from USGS, specifically Landsat 5, Landsat 7, and Landsat 8, for LULC analysis.
- The second step involved analyzing the data using a random sampling method to perform accuracy assessments and validation.
- The third step focused on correlating the remotely sensed satellite land cover changes with spectral indices, including NDVI, NDBI, NDWI, and NDBaI.
- The fourth step involved collecting quantitative crop production data from the statistics wing and water cess data from the irrigation department. The detailed methodological framework is shown in Figure 2.



Figure.1: Location Map of Tehsil D.I. Khan

### Landsat Image Pre-Processing:

GIS is applied for the analysis and Spatio-temporal representation of LULC changes in the study area using Landsat imageries. The assessment of LULC changes in the study area was formulated by implementing supervised classifier.

<b>Table 1:</b> Landsat data used						
Satellite Sensor	Spatial Resolution	AQ date	(WRS)			
Landsat 5 TM	30m ×30m	1991-4-18	WRS-2 151/37			
Landsat 7 ETM	30m ×30m	2001-3-11	WRS-2 151/37			
Landsat 5 TM	30m ×30m	2011-3-24	WRS-2 151/37			
Landsat 8 OLI/TIS	30m ×30m	2021-3-19	WRS-2 151/37			
	Satellite Sensor         Landsat 5 TM         Landsat 7 ETM         Landsat 5 TM         Landsat 5 TM         Landsat 5 TM         Landsat 5 TM	Itable I: Landsat data usSatellite SensorSpatial ResolutionLandsat 5 TM30m ×30mLandsat 7 ETM30m ×30mLandsat 5 TM30m ×30mLandsat 8 OLI/TIS30m ×30m	Satellite SensorSpatial ResolutionAQ dateLandsat 5 TM30m ×30m1991-4-18Landsat 7 ETM30m ×30m2001-3-11Landsat 5 TM30m ×30m2011-3-24Landsat 8 OLI/TIS30m ×30m2021-3-19			

Algorithms on each of the four Landsat images selected over almost 30-year period (1991–2021). Table 1, show the details of the images used in this study.

### **Process and Analysis:**

The primary objective of image classification is to automatically group similar pixels into meaningful categories or classes [22]. Image classification can be broadly categorized into two types: supervised and unsupervised classification. Supervised classification involves statistically categorizing all pixels within an image based on predefined land cover classes, using a signature file. In contrast, unsupervised classification automatically identifies and categorizes spectrally homogeneous groups into meaningful land use and land cover (LULC) classes [23].

To generate LULC thematic maps for the research region, this study employed a supervised classification technique, as described by [24], [25], and [26]. According to [27], band combinations such as color infrared 432 from Landsat TM and Landsat ETM+, and color infrared 543 from Landsat OLI, were used to delineate training areas and enhance image interpretation. This approach made sand and barren land more distinguishable (Figure 2). In the signature file, signature classes are stored, and after creating the signature file, the images were classified using the maximum likelihood classification method. This technique requires users to specify the types and numbers of LULC classes in advance [28].



Figure.2: Research Methodology flow chart

### Accuracy Assessment and Validation:

To assess accuracy, a random sampling method was utilized based on sample locations to verify the presence of various land features, including built-up areas, agricultural fields, water bodies, and barren land. During the ground verification survey, each sample site was physically inspected, and the collected data were compared with the classification results. Producer accuracy (omission error) and user accuracy (commission error) were subsequently calculated. The kappa coefficient was derived from the observed and expected classifications using a specific equation. The kappa coefficient, commonly used to summarize the accuracy of remote sensing-derived land use or land cover classifications, provides a measure of agreement between the classification results and ground truth data [29]. This metric requires a sampling model approximated by simple random sampling for accurate estimation of the kappa coefficient and its standard error [30].

### Secondary Data:

Temporal satellite images play a crucial role in monitoring crop growth, estimating crop yields, and distinguishing between different crop varieties [31][32]. Among the various indices used for analyzing remotely sensed data, the Normalized Difference Vegetation Index (NDVI) is particularly prominent. NDVI is extensively utilized to monitor crop and vegetation dynamics due to its effectiveness in providing information on vegetation health and the proportion of vegetation within a given area [33][34]. It is calculated as the ratio of the difference between the near-infrared (NIR) and red bands of satellite images to their sum [37]. NIR represents the near-infrared band and R denotes the red band [38]. The resulting NDVI values range from -1 to 1, with higher values indicating denser vegetation and lower values representing sparse or absent vegetation [39]. The crop-covered area data derived from NDVI were cross-checked with crop survey reports from the Agriculture Training Department, and the results were found to be consistent with the reports. Additionally, other indices such as NDBI (Normalized Difference



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Built-up Index), NDBaI (Normalized Difference Built-up Index), and NDWI (Normalized Difference Water Index) were also utilized to further analyze land cover changes. Analysis and Results:

# This section deal with the analysis and results. This section is classified in too many sections. The first section about overview of chashma right bank irrigation project (CRBIP). Section two deal with the impact of CRBIP on LULC dynamics. Section three deal with the LULC assessment (1991-2021). Section four describe the accuracy assement and validation. Section five deal with detection of Land use land cover (LULC) change during 1991-2021. Section six describe the spatio-temporal change in cropping pattern (1991-2021).

### Chashma Right Bank Irrigation Project (CRBIP):

The Chashma Right Bank Irrigation Project (CRBIP) is situated on the west bank of the Indus River, stretching from the Chashma Barrage in the D.I. Khan area of Khyber Pakhtunkhwa (KP) to Taunsa Sharif in Punjab. This project aimed to stimulate growth by enhancing agricultural productivity within its command area, thereby promoting job creation, boosting income, and increasing savings and consumption. Before the CRBIP, Dera Ismail Khan lagged behind other districts in the province in terms of agricultural development. Water scarcity limited irrigation options to rain and flood irrigation. Since the inception of CRBIP, it has not only provided a reliable source of agricultural water but has also served as a dependable supply of drinking water. The project has led to a tenfold increase in agricultural productivity and has significantly transformed cropping patterns and intensities. The expansion of canal irrigation has notably improved the standard of living in the area. Prior to the CRBIP, irrigation was minimal; however, the project has greatly increased the irrigated area, resulting in substantial changes in cropping intensity.

Table 2: Salient Features of CRBIP				
Length	274 Km.			
Discharge Capacity	7897 Cs.			
Cultivable Command Area	606000 Acres			
NWFP	366000 Acres			
Punjab	240000 Acres			
Distributaries	76 Nos.			
Total Length of Distributaries	1065 Km.			

**Table 2:** Salient Features of CRBIP

The Chashma Right Bank Canal (CRBC) spans two provinces and covers 250,000 hectares. The project was executed in three stages: Stage I began in 1987–88, followed by Stage II in 1989 and Stage III in 2001. Originating from the Indus River at the Chashma Barrage, the CRBC significantly transformed land use and cultivation patterns in the D.I. Khan district. Previously, a portion of the project area was irrigated by the Paharpur inundation canal, established in 1902. The CRBC aimed to boost agricultural productivity, create employment opportunities, and reduce poverty. With a discharge capacity of 138 cubic meters per second, the CRBC is a substantial irrigation system. It receives water from the Chashma Barrage on the Indus Basin, situated below the Tarbela Reservoir, which holds 0.5 billion cubic meters of water. The main canal, stretching 258 kilometers, serves 23,067 hectares across Punjab and NWFP. Water allocation is determined based on ten-day water demands for proposed cropping patterns, with winter cropping intensities at 90% and summer at 60%. Before CRBIP, D.I. Khan's cropping intensity was 28%, but the project aimed to increase it to 143%. The total project cost was \$71.5 million, with \$34.2 million in foreign exchange and \$37.3 million in local currency costs.

### Impact of CRBIPC on Land Use Dynamics:

The CRBC has significantly altered land use and cultivation patterns in the D.I. Khan tehsil. The project has expanded cultivated land and dramatically increased crop yields.



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Following the commissioning of the CRBC, prime agricultural land was converted to nonagricultural uses, and the net sown area improved. However, the shift from dry farming to waterintensive cash crops led to waterlogging and salinity issues, particularly in Stage I. Additionally, land values have risen substantially. The CRBC has been crucial in enhancing household income through increased irrigation water availability, which has led to greater spending and savings among local farmers.

### Land Use Changes Assessment (1991-2021):

Land use classification was performed using freely available satellite images from various dates. These images were processed using atmospheric, geometric, and other enhancement techniques. Supervised classification was used to categorize the images into built-up areas, vegetation cover, water bodies, and barren land. Changes in these land cover classes were analyzed to identify temporal variations in land use. In 1991, vegetation cover was concentrated in the eastern part of Tehsil D.I. Khan, with barren areas predominating in the west. By 2001, there was a noticeable increase in built-up areas from 33.8% in 1991 to 39.8%. Water bodies also increased from 3.5% to 4.3%. Barren land and vegetation cover showed no significant changes during this period. In 2011, the data revealed a gradual increase in vegetation cover in the east of Tehsil D.I. Khan, with built-up areas expanding further. The vegetation cover increased from 19.8% in 2001 to 21% in 2011. Water bodies initially increased to 4.3% in 2001 but decreased to 3.7% in 2011. The CRBC's influence led to a replacement of dry farming land with water-intensive cash crops, increasing the net sown area and land values.

By 2021, the built-up area had grown significantly to 45.9%, up from 33.8% in 1991. This increase reflects the CRBC's role in enhancing agricultural productivity and expanding cultivation. The study also highlights significant changes in water bodies over the past decade, with a noted decrease in their coverage. Overall, the analysis indicates that vegetation cover increased from 15% in 1991 to 23.4% in 2021, while barren land decreased and was repurposed for settlement expansion. Water bodies fluctuated, with a peak at 4.3% in 2001 and a drop to 3.3% in 2021. The CRBC's construction contributed to the increase in vegetation cover and the overall transformation of the land use landscape in Tehsil D.I. Khan.



Figure 3: Spatio-temporal Land use for the years 1991,2001,2011,2021

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Similarly, spectral indices were employed to validate land use and land cover classes, as illustrated in Figures 4, 5, 6, and 7. These indices serve as graphical tools to analyze remote sensing data for specific land classes. Researchers often identify the bands with the highest and lowest reflectance to construct these indices [41]. Figure 4 displays the Normalized Difference Vegetation Index (NDVI), which evaluates healthy vegetation by comparing the difference between near-infrared (NIR) and red light. The NDVI values ranged from -0.1 to 0.4 in 1991, -0.4 to 0.6 in 2001, -0.1 to 0.4 in 2011, and -0.0 to 0.6 in 2021.

Figure 5 illustrates the Normalized Difference Water Index (NDWI), used to enhance the visibility of water features in remotely sensed imagery. This index helps in distinguishing water bodies more effectively. Figure 6 presents the Normalized Difference Built-up Index (NDBI), which was utilized to extract and identify built-up areas from imagery. This index is crucial for mapping one of the major land cover types—built-up areas. The NDBI values ranged from -0.3 to 0.39 in 1991, -0.6 to 0.46 in 2001, -0.3 to 0.53 in 2011, and -0.2 to 0.59 in 2021.

Figure 7 shows the Normalized Difference Barren Index (NDBaI), which assesses the spectral characteristics of various land cover types. Developed using shortwave infrared and near-infrared bands, the NDBaI is instrumental in mapping bare terrain. These indices collectively enhance the accuracy of land use and land cover classification by providing detailed spectral information.



Figure 4: NDVI Change detection from 1991-2021

Figure 5: NDWI Change detection from 1991-2021



Figure 6: NDBI Change detection from 1991-<br/>2021Figure 7: NDBaI Change detection from<br/>1991-2021

### Accuracy Assessment and Validataion:

The accuracy assessment was performed after image classification taking 70-80 random samples for each land cover class and a total 300 samples for each image. The overall accuracy for the year 1991 was 91% with kappa coefficient 0.87, whereas the overall accuracy of the 2001 image classification was 93% with kappa coefficient value 0.9 (Table 3). The overall accuracy for the year 2011 was 88.7%, while for 2021 was 99%, whereas the kappa coefficient was 0.85 and 0.98, respectively.

 Table 3: Image classification accuracy assessment of the selected years 1991, 2001, 2011, and

 2021

2021					
Images	<b>Overall Accuracy</b>	Kappa Coefficient			
1991	91%	0.87			
2001	93%	0.9			
2011	88.7%	0.85			
2021	99%	0.98			

### Detection of Land Use Land Cover (lulc) Changes During 1991 to 2021:

The change in lulc during 1991-2021 calculated in this study, and the result showed 35.4% increase in vegetation cover of D.I. Khan Tehsil just in a time span of three decades during 1991-2021 (Figures. 8 and 9). At the same time, the gradual decrease in water bodies and barren land was observed from this study result which is 3.3% decrease in water bodies and 27.4% in barren land (Table 4). Although increase in built-up area was also observed during (1991-2021) due to spatio- temporal change of chashma right bank canal in land use land cover of D.I. Khan tehsil. Figure 4 shows the slowly and gradual increase in vegetation cover in the command area of Tehsil D.I. Khan.





**Figure 8:** Land use area in percentage during (1991-2021) **Table 4:** Land use land cover change in D.L. Khan Tehsil during 1991-2021

LULC Classification	Year 1991	Year 2001	Year 2011	Year 2021
Built up area	1124.22 (33.88)	1339.14 (39.8)	1442.62 (42.5)	1724.95 (45.9)
Barren Land	1629.9 (48.12)	1244.37 (36.1)	1092.9 (32.3)	845.52 (27.4)
Water bodies	118.8 (3.50)	144.63 (4.3)	125.5 (3.7)	101.8 (3.3)
Vegetation Cover	509.16 (15)	666.72 (19.8)	716.21 (21.1)	722.09 (23.4)
Total	3382.08			

Note that Figure. 9 a, b, c, and the d trend of land use changes 1991-2021. The graph (a) trend indicting the rapid increase in built-up area with increasing of population. The graph (b) shows the decline of barren land after 2011. The graph (c) indicating the dramatic increase of vegetation cover from 1991 to 2021. The graph (d) shows the water bodies during 1991-2021.





Figure 9: Trends of Land Use Changes during past three decades (1991-2021) Spatio-Temporal Change in Cropping Pattern (1991-2021):



**Figure 10**: (a) Kharif crop cover area in hectares, Rabi crop cover area obtained from crop reporting (b)

The analysis of cropping patterns from 1991 to 2021 reveals notable changes in crop coverage over the study period. Specifically, the area dedicated to sugarcane increased from 5,087 hectares in 1991 to 7,104 hectares in 2021. Similarly, the area under rice expanded from 4,123 hectares to 4,505 hectares. Conversely, the area covered by wheat grew significantly, rising from 55,205 hectares in 1991 to 89,445 hectares in 2021. This substantial increase in wheat cultivation can be attributed to the enhanced availability of irrigation water, which has also benefited cash crops like sugarcane. Other crops, including gram, rapeseed, mustard, and various fruits and vegetables, have also shown growth, reflecting changes in agricultural practices. Figure 10 illustrates these shifts in crop types over time. Statistical data from the Crop Reporting Department corroborates these findings, showing increased areas for wheat, sugarcane, and rice from 1991 to 2021. Figure 11 provides a comparative overview of crop yields in tons as reported by the Agriculture Department, highlighting the impact of the canal's introduction on the expansion of water-intensive crops and the increased coverage of fruits and vegetables. The detailed statistics presented in Figure 11 further emphasize the growth in crop areas and yields, confirming the significant influence of improved irrigation infrastructure on agricultural productivity.



**Figure 11**: Graphic showing cropping pattern of the study area in Hectare crop reporting **Discussion**:

The current study focused on the impact of the Chashma Right Bank Canal (CRBC) on land use change in D.I. Khan Tehsil using GIS, remote sensing, and statistical crop production data. Land use change (LUC) has garnered growing interest in recent research due to its complexity and the numerous environmental issues it presents. Evaluating the impact of irrigation projects on land use changes and cropping patterns in rainfed areas is crucial for the



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planning and management of valuable water resources for agricultural production in Pakistan. The study results indicated fluctuations in different land use classes over the past three decades (1991-2021), with a notable increase in vegetation cover.

The results showed that barren land increased in 1991, while vegetation cover and builtup areas increased compared to 2021. This increase in vegetation cover, built-up areas, and the decrease in barren land can be attributed to the implementation of the CRBC in the southern part of Khyber Pakhtunkhwa from 1984 to 2001. The area of barren land was 48.12% in 1991 and decreased to 27.4% in 2021. On the other hand, water bodies experienced slight fluctuations throughout the study period. This decline in water bodies could be due to the Indus River running dry or a reduction in their extent over time.

### **Conclusion:**

The study concluded that D.I. Khan Tehsil has experienced rapid, unplanned vegetation growth. Over the last three decades (1991-2021), the vegetation cover increased by approximately 8.8%. Satellite remote sensing imagery proves to be an effective tool for monitoring and regulating land use and land cover (LULC) changes and cropping patterns. Cropping patterns, as assessed using NDVI, indicate that there was a significant increase in agricultural area following the construction of the CRBC. Prior to the CRBC, major crops included wheat, corn, millet, and gram. However, after the CRBC's construction, these were replaced by water-loving cash crops such as cotton, rice, and sugarcane, as well as increased cultivation of fruits and pulses. The availability of irrigation water through the CRBC has not only enhanced agricultural productivity but also significantly altered land use and cropping patterns in the study area.

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