



# Quantifying irrigation water demand and supply gap using remote sensing and GIS in Multan, Pakistan

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**Abstract** Human interventions and rapid changes in land use adversely affect the adequate distribution of water resources. A research study was conducted to quantify the gap between demand and supply for irrigation water in Multan, Pakistan, which may lead to sustainable water management. Two remotely sensed images (Landsat 8 OLI and Landsat 5 TM) were downloaded for the years 2010 and 2020, and supervised classification method was performed for the selected

land use land cover (LULC) classes and basic framework. During the evaluation, the kappa coefficient was found in the ranges of 0.83–0.85, and overall accuracy was found to be more than 80% which indicated a substantial agreement between the classified maps and the ground truth data for both years and seasons. The LULC maps showed that urbanization has increased by 49% during the last decade (2010–2020). Reduction in planting areas for wheat (9%), cotton (24%), and orchards (46%) was observed. An increase in planting areas for rice (92%) and sugarcane (63%) was observed. The changing LULC pattern may be related to variation in water demand and supply for irrigation. The irrigation water demand has decreased by 370.2 Mm<sup>3</sup> from 2010 to 2020, due to the reduction in agricultural land and an increase in urbanization. Available irrigation water supply (canals/rainfall) was estimated as 2432 Mm<sup>3</sup> for the year 2020 which was 26% less than that of total irrigation water demand (3281 Mm<sup>3</sup>). The findings also provide the database for sustainable water management and equitable distribution of water in the region.

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**Keywords** Water resources · Remotely sensed images · LULC · Demand and supply gap

## Introduction

The alteration of the land surface by human intervention is known as LULC change. These are the major causes for local, regional, and global

changes in the environmental ecosystem (Hussain et al., 2020; Zappa et al., 2021; Zhang et al., 2021). The impacts of LULC changes on water balance components and groundwater levels were analyzed from 1990 to 2018 in Drava floodplains, Hungary. The decrease in total annual groundwater recharge was observed as  $5.3 \times 10^7 \text{ m}^3$  in the floodplains. Moreover, 0.1 m decline in average groundwater level was also found for the same period (Salem et al., 2023). The significant impacts land alterations on surface runoff have been reported by Mbungu (2017). It was observed that the surface runoff increased by 75% and baseflow decreased by 66% from the baseline in 2015 in Eastern Arc Mountains of Tanzania. Zappa et al. (2021) found that the irrigation requirements in terms of temporal dynamics and spatial patterns agreed with reference data with mean Pearson correlation of 0.64. Furthermore, impacts of changing land use pattern on depletion in groundwater level, increase in surface temperature, and runoff have been analyzed. The variations in groundwater level, surface temperature, and runoff can directly be related to variation in water demand and supply for irrigation especially in already water-scarce regions (Ahsen et al., 2020; Foster et al., 2020; Naeem et al., 2022; Li et al., 2022).

It has also been reported that increasing demand and supply gap for irrigation water will create water scarcity problems in coming years (An et al., 2021). A study described that with rapid increase in China's economic growth and population, the demand for water has increased. It was predicted that water consumption would reach 700–800 billion  $\text{m}^3$  per year. The water consumption has reached close of available water (800–950 billion  $\text{m}^3$  per year). The imbalance irrigation water demand and supply have reached to a dire state in China. The accurate knowledge about the supply and demand gap has become a top priority for sustainable water management (An et al., 2021; Zhu & Dou, 2018). It has been observed that eruptive population growth, deforestation, urbanization, and change in crop acreage are serious threats to sustainable water resource management (Jaiswal et al., 2003; Ke et al., 2015; Naeem et al., 2022). Similarly, changes in land use pattern significantly impact the functionality water, land, and other natural resources

management (Vivekananda et al., 2021). Therefore, accurate and timely information regarding LULC changes are very useful to quantify the agriculture water demand and supply for natural resource management (Kassawmar et al., 2018; Ahsen et al., 2020; Cutchan et al., 2021).

Remote sensing has been successfully applied by various researchers for LULC change detection and its impacts on crop water resources (Ke et al., 2015; Aik et al., 2020; Ahsen et al., 2020; Almamalachy et al., 2020). For the detection and quantification of irrigation at 500 m sampling, Zappa et al. (2021) used the spatial and temporal patterns of the TU Wien Sentinel-1 Surface Soil Moisture product. Tran et al. (Tran et al., 2020) used Landsat satellite images, GIS, and Delphi method to analyze the impacts and causes of LULC change in the coastal area of Ca Mau province for 30 years from 1989 to 2018. Moreover, landsat-8 OLI data was also used to estimate NDVI and to distinguish rice from other land use types. The crop water requirements for different crops were estimated for Summer-Autumn and Winter-Spring seasons using satellite imagery (Ahsen et al., 2020). In last 30 years, a total of 788  $\text{m}^3$  water losses were found in Multan region, Pakistan, due to LULC changes (conversion of water body into settlements, barren land, crop land, spare, and dense vegetation). These water losses are responsible for uneven distribution of available water supplies among the farming community (Naeem et al., 2022). Foster et al. (2020) applied remote sensing to identify and highlight the number of priority areas to support efforts to close gaps in accounting and monitoring of agricultural water use. Water demand is growing rapidly due to the rapid expansion of urbanization and socio-economic activities (Salehi, 2022; Saleth & Amarasinghe, 2010).

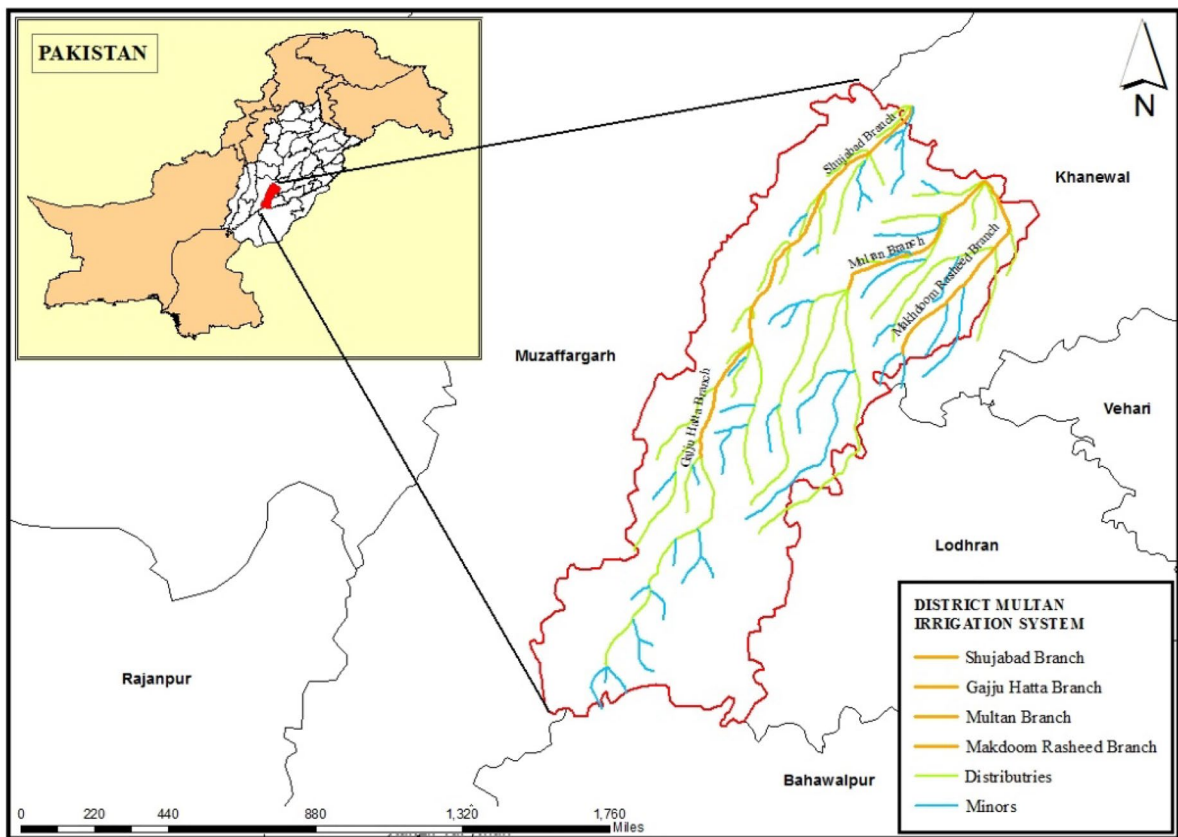
Spatio-temporal analysis of water supply and demand using remote sensing may help to support decision making for water management at watersheds and agricultural field scale (Lillo-Saavedra et al., 2021). However, most of the agricultural water use is not monitored. The limited metering of irrigation despite is increasing pressure on both groundwater and surface water resources in many agricultural regions worldwide. However, errors in irrigation supply and demand have potential to generate significant negative impacts if agricultural water users are incorrectly allowed to exceed intended abstraction limits. The accurate assessment of change in water supply and crop water

demand due the change in urban settlements and other land use types led to sustainable crop production and natural resource management and equitable distribution of water among the farmers (Angella et al., 2016; Khan et al., 2019; Naeem et al., 2022). However, no study has been conducted in the region to quantify the water supply and demand gap using remote sensing techniques. Therefore, a research study was conducted to quantify the gaps between crop water supply and demand. A comprehensive analysis of satellite-based monitoring of irrigation water demand and supply was carried out for equitable water distribution and sustainable water resource management. The validation and assessment of satellite monitoring accuracy were also carried out for judicious use of satellite data for agricultural water management and policy making.

### Methodology

#### Study area

The selected study area (Multan District) is in Punjab, Pakistan, between the latitude of 30.18° N and longitude of 71.49° E. The population of Multan District is 1.315 million. The total area of the district is spread over 3721 Km<sup>2</sup>. Multan has four tehsils namely Multan City, Multan Saddar, Shujabad, and Jalalpur Pirwala (Fig. 1). It is surrounded by the Khanewal District to the North and North-East, the Vehari District to the East, and Lodhran District to the South. Multan has a rich network of irrigation systems consisting of four branch canals. The Chenab River flows on its Western side, across which lies Muzaffargarh District (Ahsen et al., 2020).



**Fig. 1** Location of study area (Multan, Pakistan) and irrigation system

## Cropping pattern

Major crops contributing to the cropping pattern in the study area are wheat, cotton, sugarcane, rice, maize, fodder crops, etc. Cotton is the main cash crop of the Kharif season, although wheat is the principal crop for the Rabi season. The main area of the Multan district follows the cotton-wheat cropping pattern. However, the cropping pattern is moving to rice-wheat and sugarcane-wheat-cotton due to the excessive production price of cotton and change in climatic situations. There are other crops like corn, sorghum, millet, and forage planted at some places in the study area. Orchards of mangoes and citrus fruits are also an important component of Multan's overall agricultural production.

## Climate

The study area is in an arid climate region with moderately severe weather conditions in summer and winter. It typically experiences strong storms caused by extreme events throughout the year. Over the last 30 years, Multan's climate has undergone several changes, including an increase in temperature and a decrease in rainfall. According to a recent study by Hussain et al. (2020), the average temperature in Multan has increased by 1.1°C over 30 years during 1990–2020. This increase in temperature is in consistent with the global trend of rising temperatures due to anthropogenic greenhouse gas emissions. The increase in temperature has also led to an increase in the frequency and intensity of heat waves. The highest and lowest average winter temperature is 23.4°C and 4.8°C, and highest and lowest average temperature in summer is 47°C and 26°C, respectively (Ahsen et al., 2020). Multan's average rainfall has decreased by 2.2 mm over the last 30 years. Rainfall occurred

with an average depth of 186 mm. That contributed to changes in the monsoon winds, which have resulted in a shift in the timing and intensity of rainfall in the region. These changes have significant implications for the region's agriculture, water resources, and human health (Hussain et al., 2020).

## Data collection

For the present study, the data is acquired mainly from three different sources. Satellite data obtained as high-resolution remote sensing imagery can be downloaded for free on [www.glovis.usgs.gov](http://www.glovis.usgs.gov). The satellite data for Landsat 5 Thematic mapper and the Landsat 8 operational land imager (OLI) with 30 m resolution, 07 bands, and 11 bands, respectively, were acquired for the LULC analysis of the study area for the period of 2010 and 2020. The required agricultural data like canal water discharge, crop coefficients, and crop calendars were obtained from the concerned agricultural departments, in Pakistan. Precipitation data were obtained from the meteorological station of Agricultural Engineering Department, Bahauddin Zakariya University (BZU) Multan, Pakistan. The details of data for each department are summarized in Table 1.

## Satellite data processing

The processing of satellite data is an important part of the LULC research and analysis of a particular study area. For this purpose, two remotely sensed images were downloaded of path/row of 150/39 and 150/40, respectively, to cover the whole study area. The downloaded images were then processed in Erdas Imagine 15. Different preprocessing tools were used for layer stacking (to combine the different band images into a single multi-band image), mosaicking (for the union of two images of different paths/row), and a subset

**Table 1** Data collection from different sources

Sources	Components	Acquisition date
Satellite data ( <a href="http://glovis.usgs.gov">glovis.usgs.gov</a> )	Landsat 8 Operational Land Imager (OLI) Landsat 5 Thematic Mapper (TM)	Feb 2020, Sep 2020 Feb 2010, Sep 2010
Agriculture data (Agricultural Department)	Average required crop water depths data, Crop Calendar	For the year of 2010-2020
Water supply (Irrigation Department, Punjab, Pakistan & BZU Weather Station)	Canal water discharge supply Monthly accumulated rainfall data	Data acquired on daily and monthly bases for the year 2020

of the final image of the study area. Integration of remote sensing and GIS such as acquisition and storage dissemination of spatial data are the tools that are used in the data interpretation analysis (Ehlers et al., 1991). The basic framework is displayed in Fig. 2. It represents the processing of satellite data, supervised classification, and data analysis.

#### Land use-land cover classification

After the processing of the satellite data, a multi-band raw image of the study area was classified by supervised classification. The method is used for identification of LULC features. The main principle of supervised classification was performed based on training class which provides a direction to classify the remotely sensed image corresponding to the same pixels grouped to form a specific LULC class. Supervised classification of the image for the year 2010 and 2020 was done through data collected from an extensive field survey of the study area (Kumar et al., 2008). The sample training classes were assigned to a specific land use feature which is used to create a signature file in the software. The signature file classifies the pixels with the same spectral characteristics into a specific LULC class. Among the different supervised classification methods, the most applied algorithm is maximum likelihood classification (MLC), especially for the characterization of agricultural areas (Silva et al., 2020). The method uses the probability function as the base for assigning a class to the image. Based on the probability theory, assumes that a certain pixel belongs to a specific class. MLC demonstrates the importance of the prior class of probability in the classification (Shivakumar & Rajashekararadhya, 2018). If the probability is lower than the specified threshold value, then the given pixel will remain unclassified.

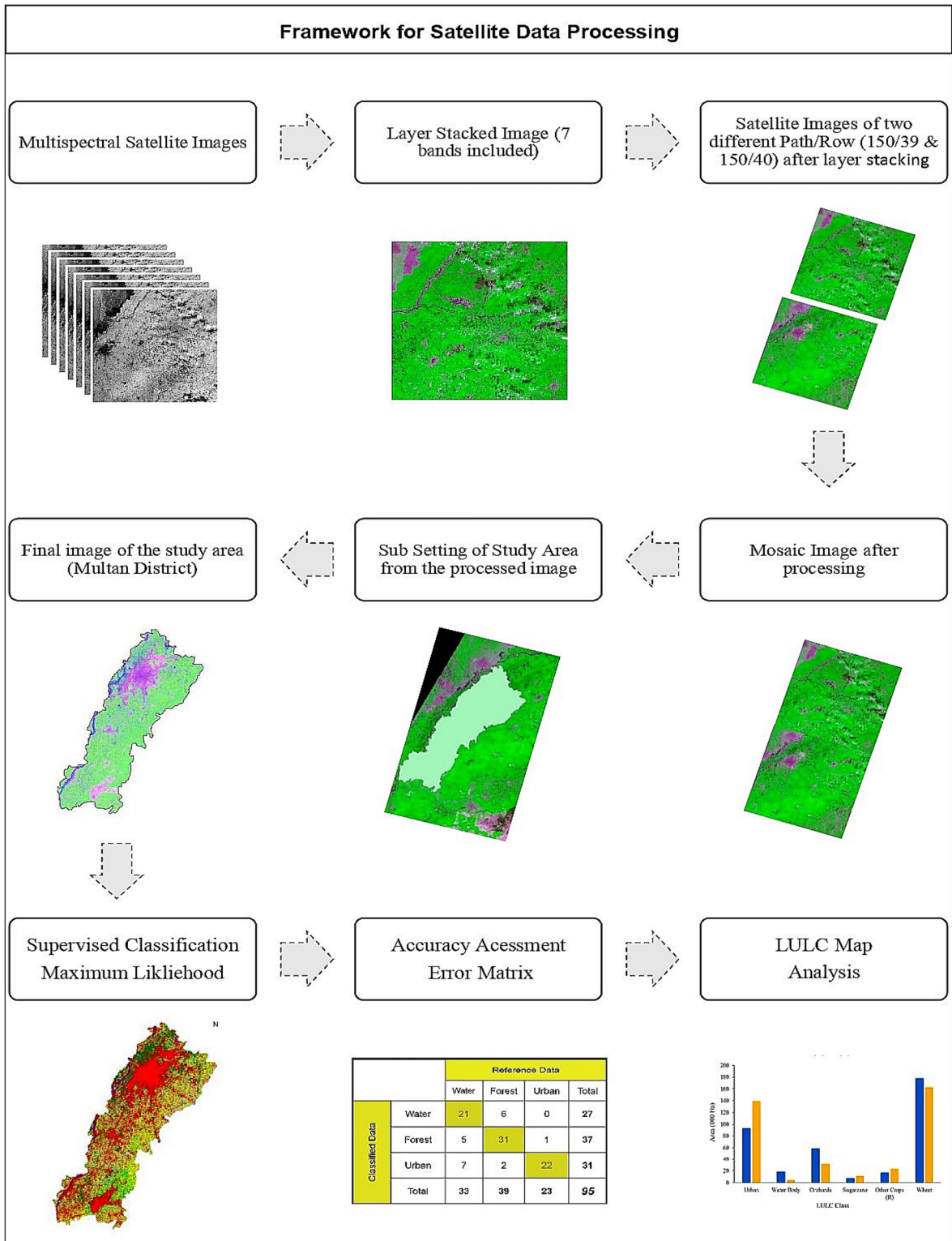
The major crops were selected according to the local cropping pattern of the study area. Six classes were identified for the Rabi season which includes urban, river, orchards, wheat, sugarcane, and other crops, and 7 classes were plotted for the Kharif season which includes urban, rivers, orchard, cotton, rice, sugarcane, and other crops (Table 2). For sowing and harvesting time of different crops, the crop calendar data of the study area was acquired from the concerned department (Table 3).

#### Accuracy assessment for the validation of LULC classification

Classification accuracy is critical to obtained results, and its impact on reliability is very important (Khan et al., 2020). Accuracy assessment provides validation to land use maps, and it is very important for the authenticity and reliability of LULC map. However, no method is accurate enough to assess the absolute accuracy of the classified image. The error matrix technique, also known as the confusion matrix, is relatively accurate and commonly used which provides considerably good results. Several ground truth points were selected for accuracy assessment (48 for urban settlements, 9 for water bodies, 74 for vegetation (field crops), 28 for wheat, 12 for rice, 17 for cotton, 9 for sugarcane, 8 for other crops, and 19 for orchards). The acquired data and survey results were then compared with the LULC map in ArcGIS 10.4 software and validated the selected points upon the specific classified class. The producer's accuracy and user's accuracy for each separate class were calculated for the years 2010 and 2020 through the error matrix method. User accuracy was very important for the assessment of assigned ground truth points on the LULC classified map. Producer accuracy was an important parameter in the evaluation of LULC map authenticity which determines the extent to which a map can be accurate for the actual features in the real world. Kappa coefficient (K) was measured to evaluate the agreement between the classified map and ground truth values; if the kappa value is 1, then there was 100% agreement, and if it was 0, then no agreement happened between the classified LULC map and the referenced ground truth values.

#### Crop irrigation water demand

The irrigation water demand in the study area for different crops (wheat, rice, cotton, sugarcane, other crops, and orchards) was estimated. The average crop water depth required in the study area is 480, 1500, 700, 2100, 800, and 1850 mm for wheat, rice, cotton, sugarcane, other crops, and orchards, respectively (Shahbaz & Ata, 2014; Ahsen et al., 2020). These values were assigned based on the available literature and validated by the regional agriculture department. Crop irrigation water demand was calculated for the years 2010 to 2020 for the evaluation of impact of



**Fig. 2** Basic framework for satellite data processing and LULC classification

change in cropping pattern on overall demand. The total crop irrigation water demand (CIWD) was calculated in (m<sup>3</sup>) through the multiplication of area of each crop calculated from LULC map and the average required crop water depth of that specific crop.

Water supply

Supply from canal irrigation system

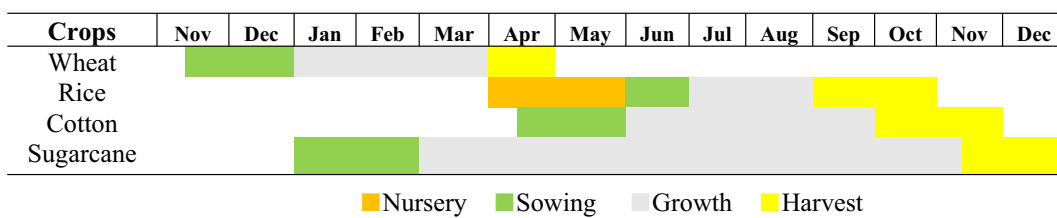
The study area has a rich system of canal irrigation systems, and the parent channel is the Sidhna Canal which originates from the Ravi River. It directs 4 branch canals (Shujabad Branch, Gujju Hatta Branch, Multan Branch, and Makhdoom Rashid Branch) into the study area District Multan (Table 4). The entire canal irrigation system in the study area is managed

by the provincial irrigation departments. Shujabad and Gujju hatta branches are non-perennial canals, and Multan and Makhdoom Rashid branches are perennial. The data was acquired on daily basis from the Punjab Irrigation Department for the year 2020 for the assessment of the canal water supply in Multan. Monthly discharges were calculated from the sum of the daily discharge data. The Shujabad branch has the maximum command area, the Gujju Hatta branch which emerges from it and starts to flow downward side which irrigates the lower parts of the study area in Shujabad and Jalalpur tehsils. Assessment of water supplied to the study area for the year 2020 was done through the evaluation of discharge from the branch canals to estimate the total water availability. The discharge from canals is allocated based on the percentage of water demand of each crop (wheat, cotton,

**Table 2** LULC Classes for Rabi & Kharif season

No.	Class	Description
1	Urban	Built-up roads, industrial areas, and residential areas etc.
2	Water Body	Rivers, streams, lakes, reservoir, ponds, tank etc.
3	Orchards	Mango, citrus and all other fruits.
4	Wheat	Wheat fields
5	Sugarcane	Sugarcane fields
6	Cotton	Cotton fields
7	Rice	Rice fields
8	Other crops	Maize, Barley, Sorghum and other fodder crops etc

**Table 3** Crop calendar of District Multan, Pakistan



**Table 4** Detail of selected canals for water supply assessment in District Multan

No.	Main canal	Branch canal	Location	Flow type	Command area (Acres)	Assign discharge (Cusecs)
1	Sidnahi	Shujabad Br.	Head	Non Perennial	8270.38	1918
2	Sidnahi-Shujabad	Gujju Hatta Br.	Tail	Non Perennial	3962.42	700
3	Sidnahi	Multan Br.	Head	Perennial	9276	775
4	Sidnahi	Makhdoom Rashid Br.	Head	Perennial	3509	425

rice, sugarcane, other crops, and orchards) in the Rabi and Kharif seasons. To calculate the water supplied from the discharge for a specific crop, the “Irrigation Equation” was used by USDA (2005); irrigation water depth supplied through canals was obtained according to the area, crop period, and allocated discharge for each crop. The irrigation water depth was then multiplied by area of each crop calculated from LULC map to estimate the water supply in (m<sup>3</sup>) that specific crop.

#### *Supply from rainfall*

The other source of water supply in the study area was rainfall. Rainfall plays an important role as an add-on in irrigation water supply and in assessing the impact on overall crop yield (Akhtar & Athar, 2020). In Pakistan, precipitation occurs most frequently in the monsoon season (Ahmad et al., 2019). For the evaluation of the water supply from precipitation, the monthly accumulated precipitation data were obtained from the meteorological station of Agricultural Engineering Department, Bahauddin Zakariya University Multan, for the year 2020. The data was also validated using data from the Pakistan Meteorological Department (PMD), which showed similar precipitation patterns at Multan. The rainfall supply for each crop was calculated in volume (m<sup>3</sup>) through the multiplication of the area of each crop obtained from the LULC map to the total rainfall that occurred during the crop period of that respective crop. The seasonal and annual water supply was estimated, adding to the total canal irrigation water and rainfall supply in the study area.

#### Demand/supply gap quantification

Quantification of the gap between water demand and supply is critical to the appropriate planning and judicious use of these available water resources (Sidhu et al., 2008). Proper agricultural management improved the quality of life (Fraiture et al., 2010). The gap between demand and supply was quantified for 2020 for effective water management in the study area. For the assessment of the demand and supply gap in 2020, results of calculated irrigation water demand and total irrigation water supply (canals and rainfall) were compared seasonally and annually in the study area. This study investigated the demand

and supply gap on volume bases; therefore, the supply was estimated based on design discharge without considering the canal losses.

## Results and discussion

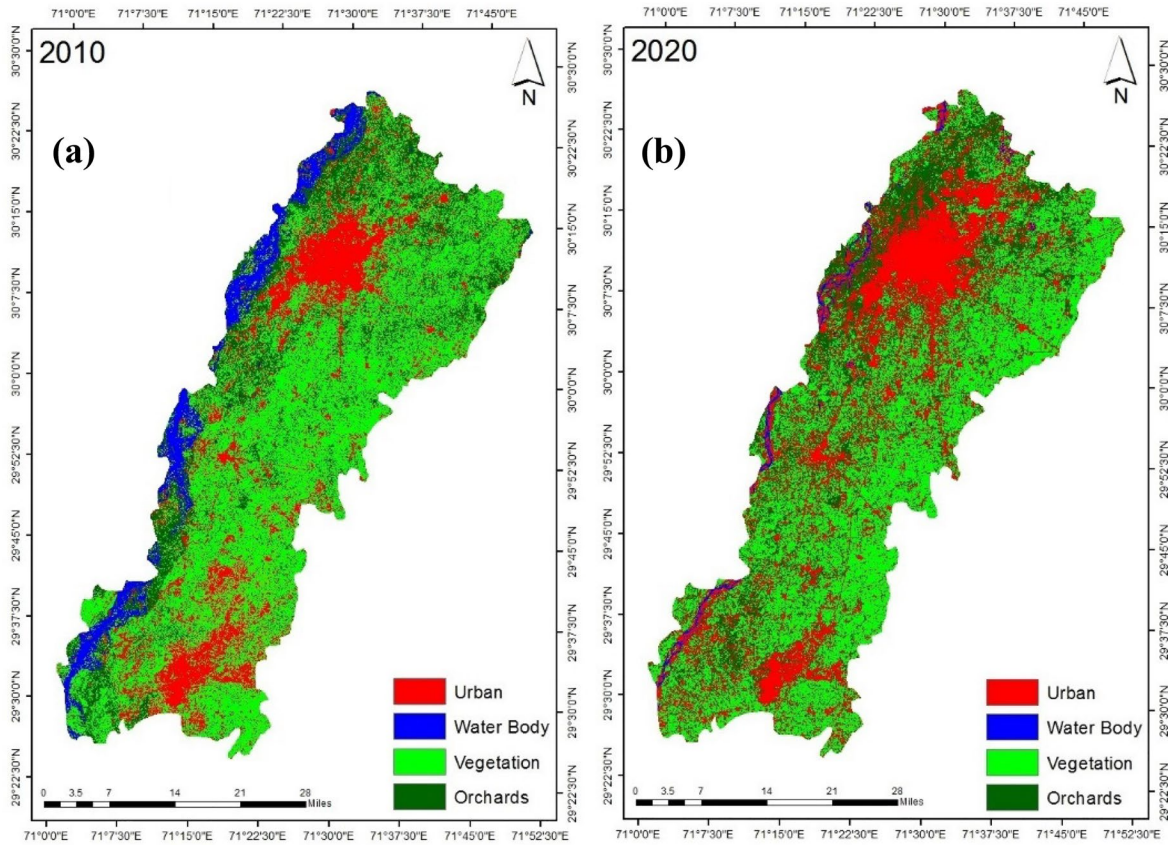
### LULC classification

General LULC classification of the study area for 2010 (Fig. 3a) and 2020 (Fig. 3b) presents 4 main classes (urban, rivers, orchards, and field crops). Table 5 depicts the changes in each LULC class for the study area from 2010 to 2020. LULC results also show most of the orchard’s area in the north-western side of the Multan along the Chenab River. Orchards include mainly mangoes and citrus fruits, which are the major component of Multan’s overall agricultural production (Naeem et al., 2022). It was observed that the area under orchards has decreased by 47% from 2010 (Fig. 4a) to 2020 (Fig. 4b). The increase in the urban settlement was observed (49%) from 2010 (Fig. 5a) to 2020 (Fig. 5b). The water body mainly consists of the river Chenab in the region that flows through the western side of the study area. A 77% decrease in the area for water bodies was observed from 2010 to 2020. The highest relative change in the area was observed for water bodies from 2010 to 2020.

### Crop classification and area assessment

For crop classification, six (06) classes (urban, water body, wheat, orchards, sugarcane, and other crops) were selected for the Rabi seasons of 2010 (Fig. 6a) and 2020 (Fig. 7a). Similarly, seven (07) classes (urban, water body, cotton, orchards, sugarcane, other crops, and rice) were selected for the Kharif season of years 2010 (Fig. 6b) and 2020 (Fig. 7b) including 4 general LULC classes. Table 5 depicts the change in planting area of major Rabi and Kharif crops from 2010 to 2020. Spatial distribution maps identified the change in spatial pattern for each crop in both the seasons from 2010 to 2020. In the Rabi season, wheat is the most important crop of the study area because the Multan region produces wheat on a large scale. It was observed that planting area for wheat has reduced to 9% from 2010 (Fig. 8a) to 2020 (Fig. 8b). The change was due to the farmer’s





**Fig. 3** General classification for LULC changes in Multan region (a) for 2010, and (b) 2020

adaptation to different crops and urbanization. Sugarcane is a perennial crop that is recurring throughout the year. The planting area for sugarcane has reached

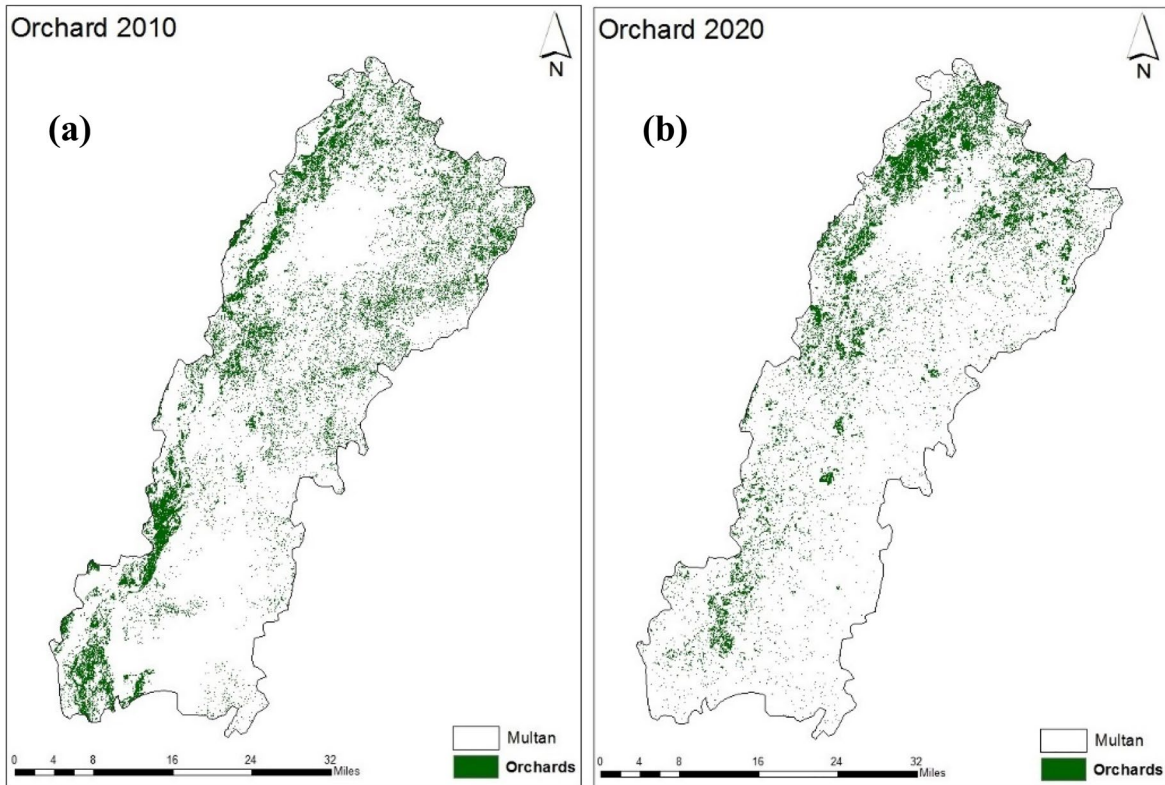
to 63% during the last decade from 2010 (Fig. 9a) to 2020 (Fig. 9b). Cotton and rice are the major crops of the Kharif season. The 24% reduction in the cropped areas of the cotton crop (Fig. 10a and b) and 92% increase in planting areas for rice crop (Fig. 11a and b) were observed from the years 2010 to 2020.

**Table 5** LULC area distribution and change detection from 2010 to 2020

Class type	LULC area distribution		Change detection	
	2010 (000 ha)	2020 (000 ha)	2010-2020 (000 ha)	(%) Area
Urban	93.4	139.2	45.8	49 ↑
Water Body	18.6	4.2	-14.4	78 ↓
Orchards	59.3	31.5	-27.8	47 ↓
Sugarcane	6.9	11.3	4.4	63 ↑
Other Crops (R)	16.6	23.4	6.8	40 ↑
Other Crops (K)	18.5	26.8	8.3	44 ↑
Cotton	152.3	115.5	-36.8	24 ↓
Rice	22.7	43.6	20.9	92 ↑
Wheat	177.5	162.8	-14.7	09 ↓

Accuracy assessment

Accuracy assessment for the classified LULC map is given in Tables 6 and 7. The average producer accuracy was 85.3%, indicating that 85.3% of the LULC features are matched with the original value on the map or Rabi season of 2010 and 2020. The average user accuracy showed that 84.1% of the total features are identified on the LULC classified map. The overall user accuracy of the LULC classified maps for the Rabi season in 2010 and 2020 were 84.9% and 85.7%, respectively. These values indicate the percentage of correctly classified pixels in the entire map for a particular season and



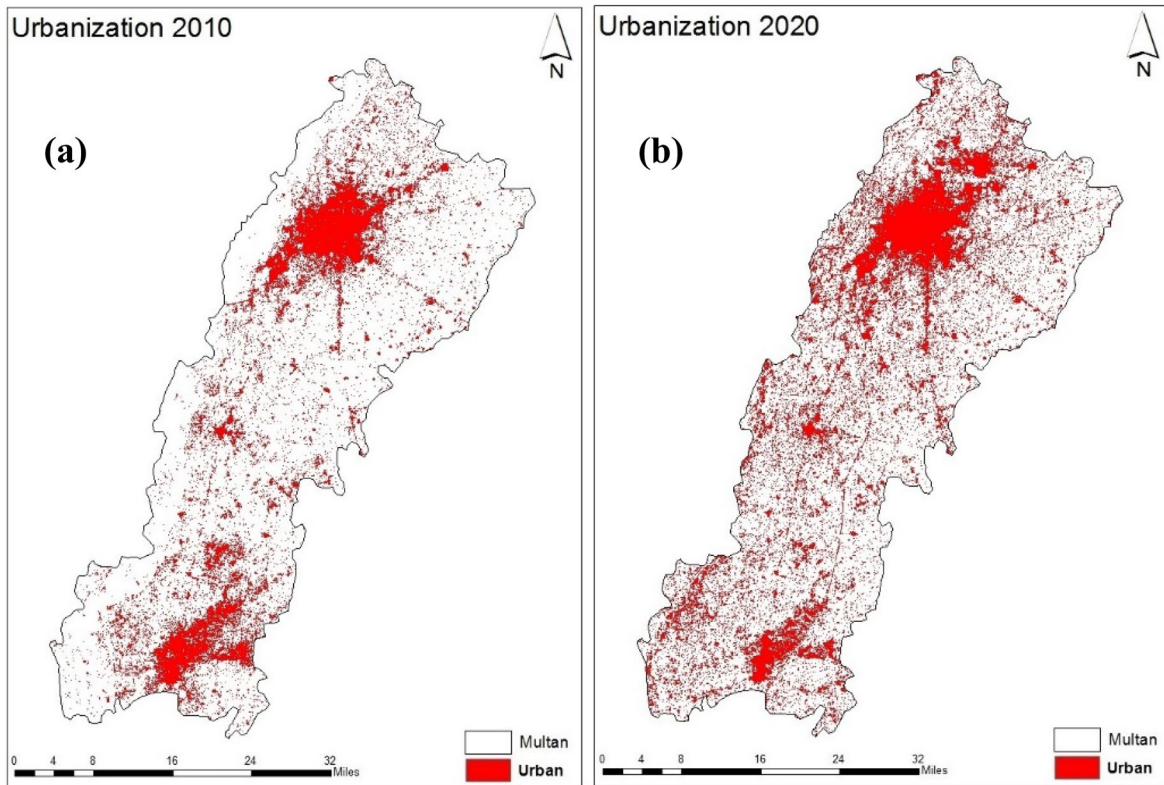
**Fig. 4** Land cover changes maps for orchard, (a) orchards area in 2010, (b) orchards area in 2020

year. Avg. producer and user accuracy for the Kharif season were found to be 83.2% and 82.5% during the last decade (2010–2020). In this case, the Kappa coefficient values for the Rabi season were 0.78 for 2010 and 0.83 for 2020, which indicates a substantial agreement between the classified maps and the ground truth data for both years. For the Kharif season, the Kappa coefficient values were 0.83% and 0.85% in 2010 and 2020, respectively. These values also indicate a substantial agreement between the classified maps and the ground truth data for both years.

#### Crop irrigation water demand

The estimated individual, seasonal and annual crop water demand for cotton, rice, wheat, sugarcane, orchards, and other crops in the region for the years 2010 and 2020 are summarized in Table 8. Results demonstrated that 92% planting area for rice has increased from 2010 to 2020 in Multan region. As a result of the increase in planting area, the irrigation water demand

for rice has also increased to 92%. Similarly, sugarcane planting area has increased to 63% along with an increase in irrigation water demand (64%) for the sugarcane. The increase in planting area (10.7%) for sugarcane and cotton has also reported in Pakistan. These are high water consumption crops; increasing planting area of sugarcane and cotton also induces a considerable increase in the irrigation water requirement and affects the planting of food crops as well as regional food security (Li et al., 2022). Similarly, rice and sugarcane are also high-water demanding crops as compared to the other crops like cotton, wheat, and orchards. However, the total irrigation water demand has reduced to 11% during the last decade from 2010 to 2020 due to an increase in urbanization and a change in cropping patterns. Seasonal irrigation water demand for Rabi is less than Kharif season in the Multan region for both the years (2010 and 2020). Both the higher water demanding crops (rice and cotton) were grown in Kharif season; therefore, the water demand was higher during the Kharif seasons of years 2010 and 2020.



**Fig. 5** Land cover changes maps for urban development (a) urbanization in 2010, (b) urbanization in 2020

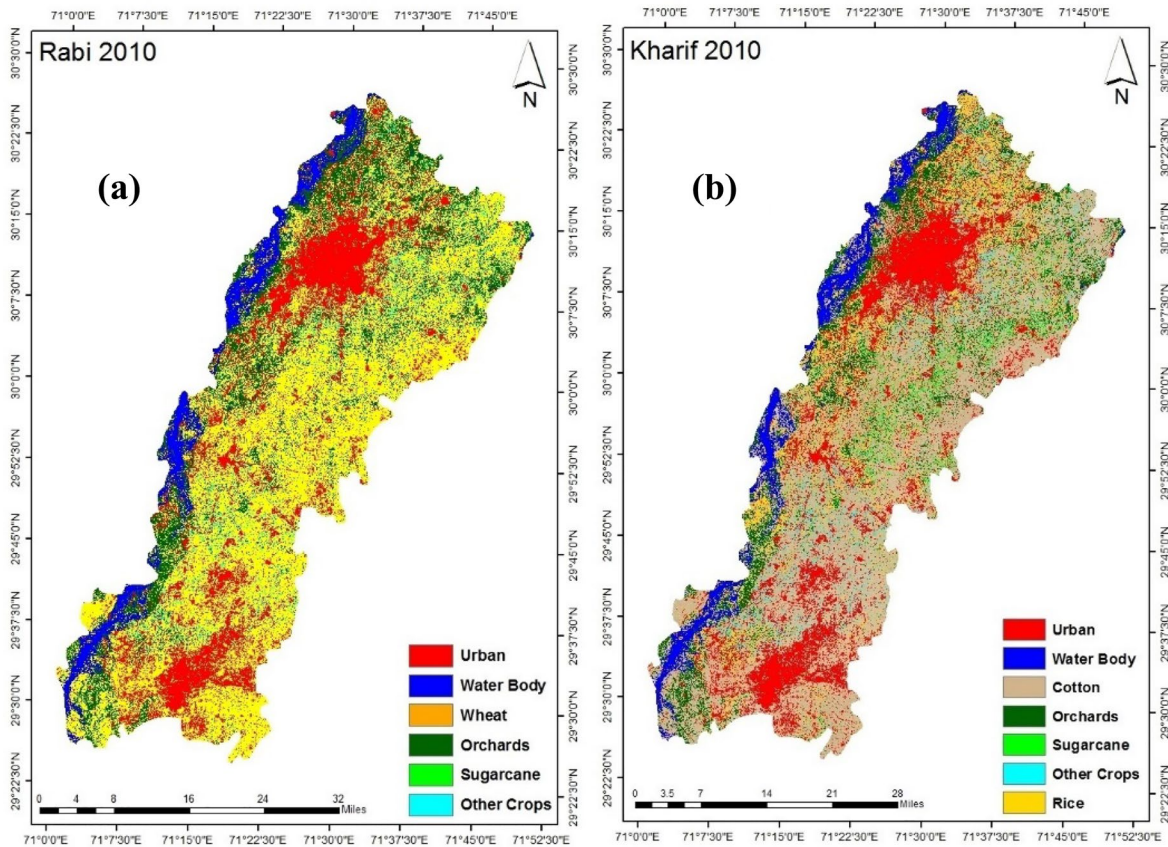
### Water supply

The monthly canal water discharge from all branch canals in 2020 was estimated (Fig. 13). The total annual water supply from the canals for the study area was found 1866.9 Mm<sup>3</sup>. Two of the branch canals were non-perennial. The discharge for these canals was relatively low in the Rabi season as compared to the Kharif season. The peak of canal water discharge was observed from May to August in 2010 and 2020. Similarly, January and March (2010 and 2020) operated at the lowest canal discharge during the year. The details of seasonal and annual canal water supply are summarized in Table 9. It was observed that wheat had the maximum canal water supply during the Rabi season as compared to the other crops. The higher canal water supply (221.4 Mm<sup>3</sup>) for wheat is due to the more planting area for wheat in the Multan region as compared to the other crops. Sugarcane is a perennial crop that starts in February and ends in December; the irrigation water demand for sugarcane gets a

peak in the summer season. The details of seasonal and annual rainfall water supply are summarized in Table 9. In the Rabi season, wheat has the maximum water supply by rainfall due to its larger planting area, and more rainfall was received in March 2020. The data showed that the maximum rainfall occurred in the Rabi season. The total annual water supply from rainfall for the study area was found to be 565.1 Mm<sup>3</sup>.

### Quantification of demand and supply gap

Details of the demand and supply gap for each specific crop and the total gap quantified for the year 2020 are summarized in Table 10. The results showed that a maximum gap was observed for wheat in the Rabi season which was 304.8 Mm<sup>3</sup> due to the relative canal water supply. Orchards showed a significant amount of demand and supply gap which was 198.3 Mm<sup>3</sup> because orchards need water throughout the year and the irregular canal water supply to orchards than crops were the



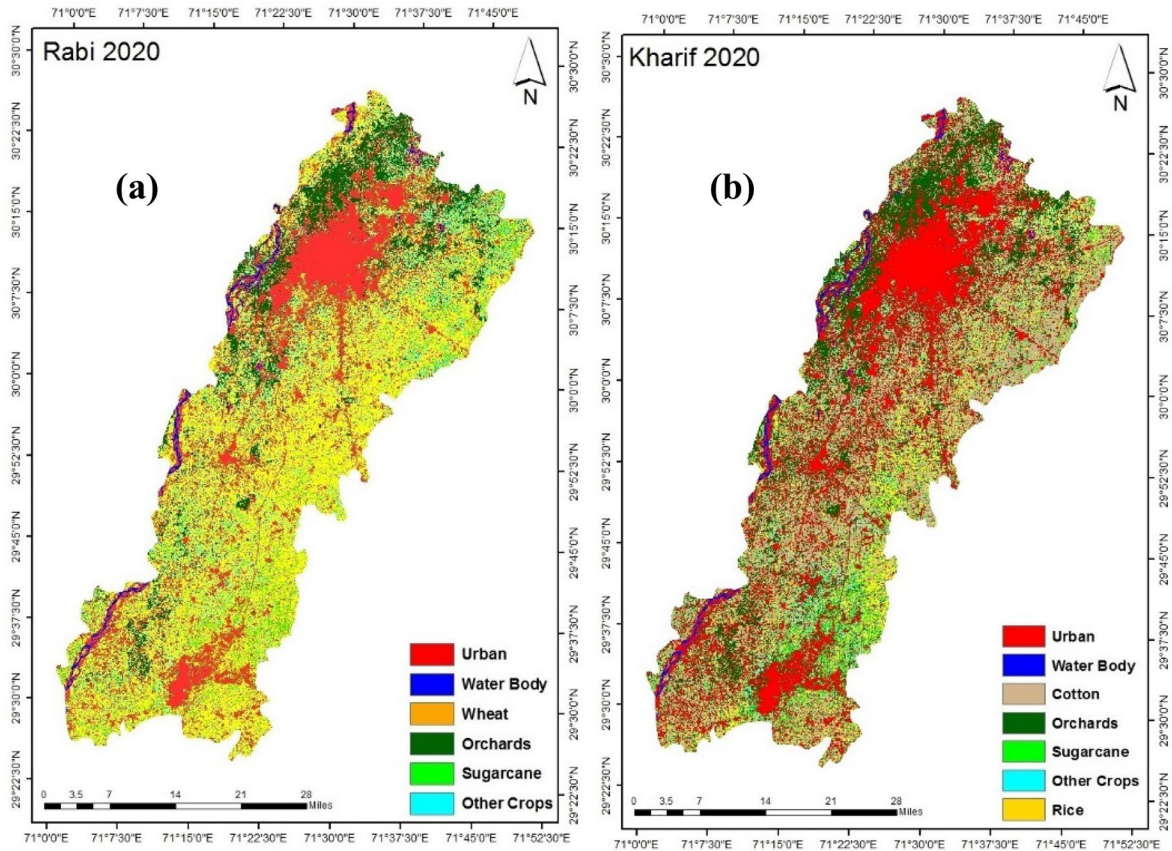
**Fig. 6** Seasonal LULC changes maps for Multan region (a) for Rabi season in 2010, and (b) Kharif season in 2010

reason for the noticeable demand and supply gap. In the Kharif season, due to canals operating at more discharge and a significant amount of rainfall occurring during the monsoon season, the demand and supply gap was less for cotton, rice, and sugarcane than that of wheat in the Rabi season. The gap for other crops was formulated for the whole year (2020) including both seasons. The total annual irrigation water demand was found to be 3280.7 Mm<sup>3</sup>, and the total water supplied from (canals and rainfall) was 2432 Mm<sup>3</sup> without losses. The total demand and supply gap as quantified was 848.7 Mm<sup>3</sup> in the Multan region in 2020.

## Discussions

The quantification of gap between demand and supply for irrigation water in Multan, Pakistan, may

lead to sustainable water management. Two remotely sensed images (Landsat 8 OLI and Landsat 5 TM) were downloaded for the years 2010 and 2020, and supervised classification method was performed for the selected LULC classes. During the evaluation, the values of Kappa coefficient, producer, and user accuracy indicate a substantial agreement between the classified maps and the ground truth data for both years. It has been reported that the Kappa coefficient is a statistical measure of agreement between the classified map and the ground truth data. It considers the agreement that could occur by chance and provides a more accurate evaluation of the map's accuracy than just the overall accuracy. A Kappa coefficient of 1 indicates perfect agreement, while a value of 0 indicates no agreement beyond chance (Kafy et al., 2023; Nguyen et al., 2020; Vanbelle & Albert, 2008). Overall, measured values of these metrics show that the LULC classified maps are relatively accurate and



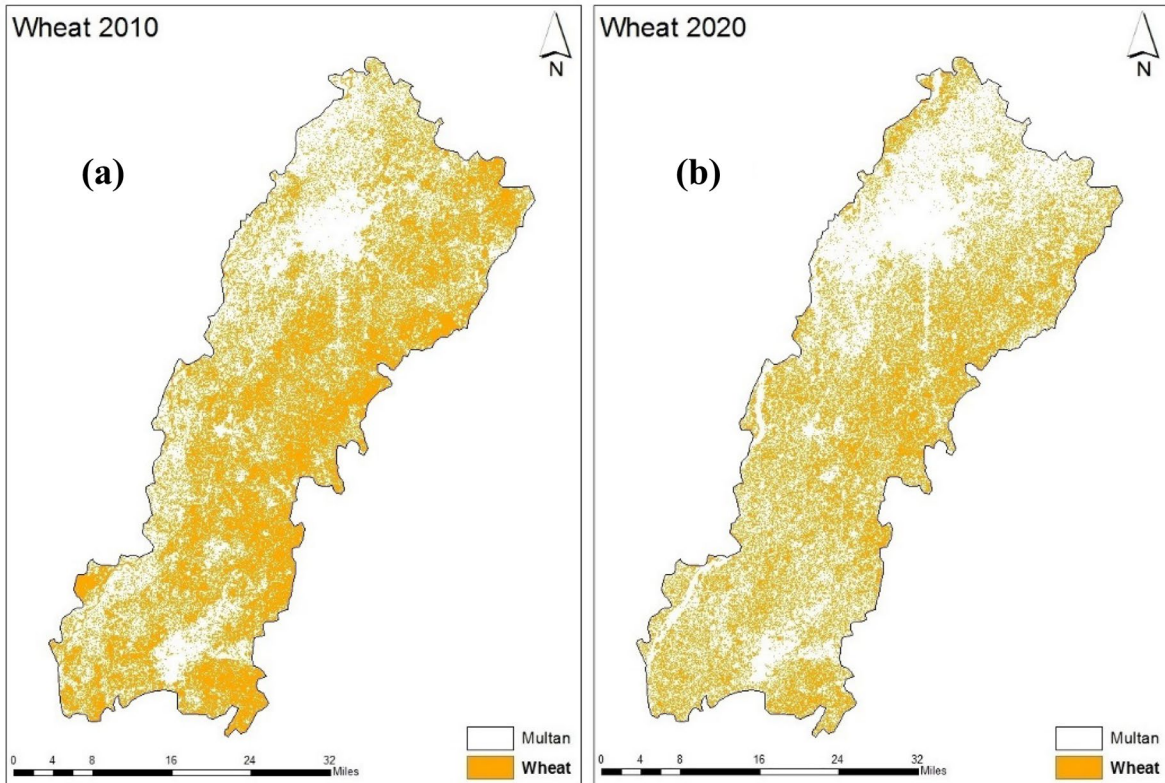
**Fig. 7** Seasonal LULC changes maps for Multan region, (a) for Rabi season in 2020, (b) Kharif season in 2020

reliable. The LULC analysis showed that the highest relative change in the area (78%) was observed for water bodies from 2010 to 2020 (Table 5). It has been reported that the water in river Chenab covers a large area in 2010 as compared to year 2020. The main reason for the larger area occupied by the river in 2010 is because of the floods which occurred during this period in Pakistan (Sajjad et al., 2020).

Overall, a 7.5% decline in area of water bodies was observed in last three decades (1990–2020) due to urban development and population growth. The reduction in area of river may also be due to change in river regime, construction of flood bunds, and reduction of river flow (Wrzesiński & Sobkowiak, 2020). However, urbanization is the important factor in region that can be considered in land use planning and sustainable water resource management (Saleth & Amarasinghe, 2010). It also gives a relative assessment of the other land use features. It has been

reported that the LULC changes have a significant impact on the functionality of land, water, and other natural resources. From the total water supply, the 788 m<sup>3</sup> lost due to LULC changes were observed (conversion vegetation and orchard to urban area) during the last three decades (1990–2020). The results indicated that the volume of water is not reaching equitably to the farming community. Therefore, there is a strong need for reallocation of water among the farmers in an equitable way. In addition, accurate assessment of change in water allocation and crop water requirement due the change in urban settlements and other land use types led to sustainable crop production, natural resource management, and equitable distribution of water among the farmers. (Khan et al., 2019; Ahsen et al., 2020; Foster et al., 2020; Vivekananda et al., 2021; Naeem et al., 2022).

The ever-increasing demand for food and rapid increase in urbanization led to uncertainty in food

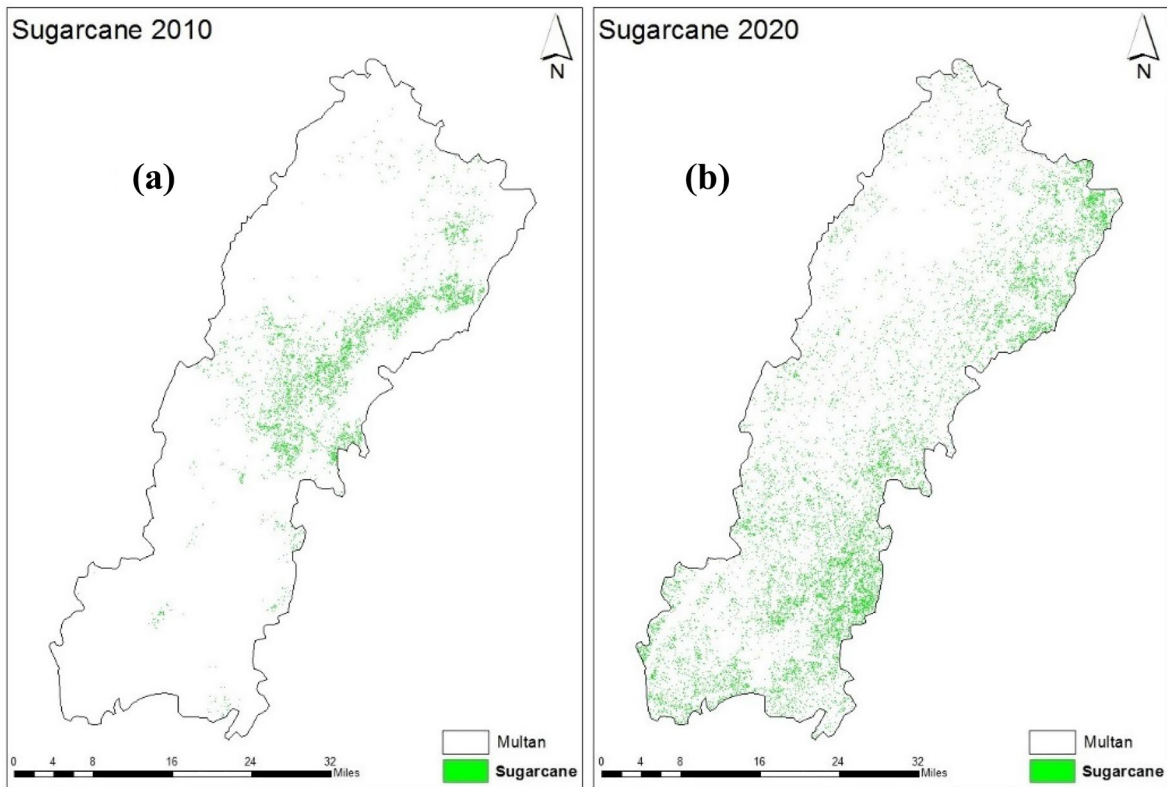


**Fig. 8** LULC change map for wheat in Multan region (a) wheat crop in 2010, (b) wheat crop in 2020

security and sustainability. Understanding the change in spatial and temporal pattern of vegetation (agriculture and fellow land), orchards, water bodies, and other landscape features associated with urbanization is vital for sustainable development especially in developing countries. There is a strong need to focus on the sustainable production of crops and the conservation of natural resources with minimum environmental impact (Nguyen et al., 2020). The reason for the reduction of the cotton crop was due to the major change in the rice crop area, and some other crops area like maize and sorghum replaced the cotton crop during the last decade (Li et al., 2022; Naeem et al., 2022). The climate change, increase in pest-insect attack, and lack of good quality seed were the other reasons for planting area of cotton crop (Arshad et al., 2021). The cropped area of rice increased by 92% during the 10 years from 2010 (Fig. 11a) to 2020 (Fig. 11b) as rice is an important crop in the Kharif season. There was a change detected in the planting area of other crops like maize millet, sorghum,

and fodder during the last decade (2010–2020). The planting area for other crops has increased by 40 to 44% in Rabi and Kharif seasons from 2010 (Fig. 12a) to 2020 (Figs. 12b and 13). The change was due to the reduction in the cropped area of orchards and converts it into urbanization. Mohsin et al. (2021) reported that planting area for orchards has reduced due to development of housing colonies, the lack of labor availability, and relatively less income from other uses of land.

Overall, urbanization is the major factor for the uncertainty in the cropping pattern change which ultimately affects the water demand and supply which is a threat to sustainable water resource management (Khan et al., 2019; Nguyen et al., 2020; Salehi, 2022). However, the total irrigation water demand has reduced to 11% during the last decade from 2010 to 2020 due to an increase in urbanization and a change in cropping patterns (Ahsen et al., 2020; Nguyen et al., 2020; Hou et al., 2021; Zappa et al., 2021). Seasonal irrigation water demand for Rabi is less than

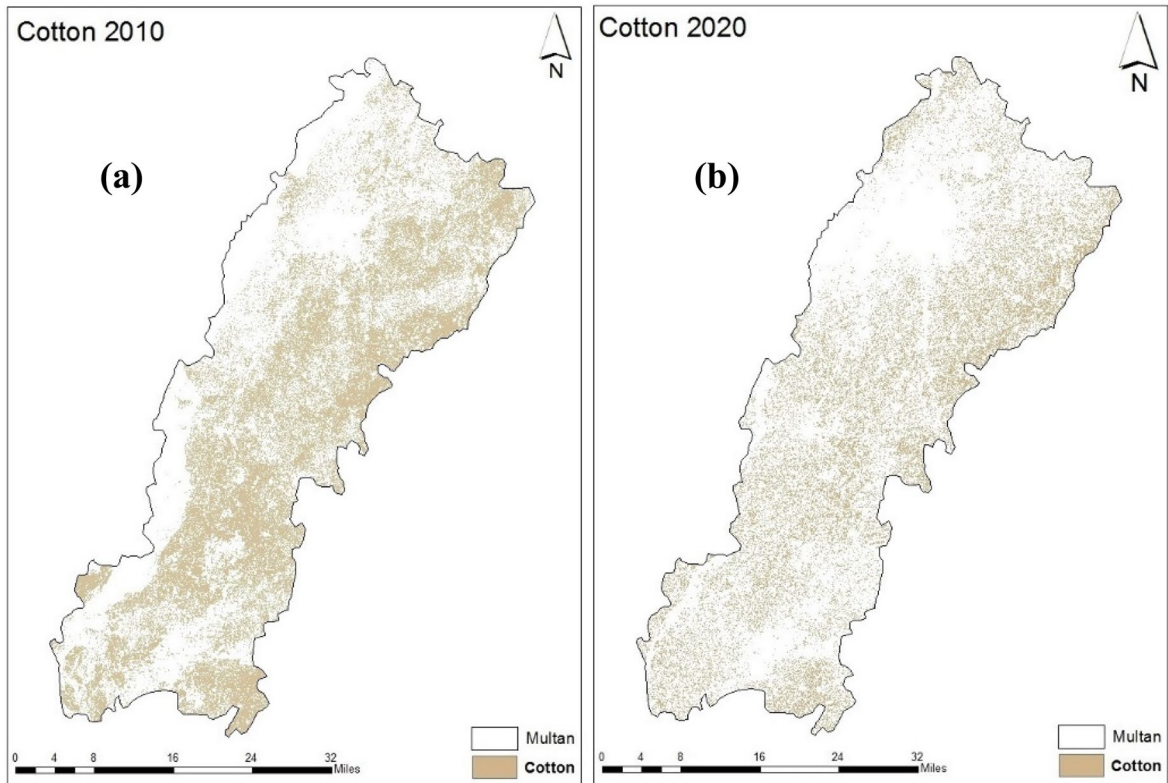


**Fig. 9** Land cover changes maps for sugarcane in Multan region (a) sugarcane in 2010, (b) sugarcane in 2020

Kharif season in the Multan region for both the years (2010 and 2020). Both the higher water demanding crops (rice and cotton) were grown in Kharif season; therefore, the water demand was higher during the Kharif seasons of years 2010 and 2020. Furthermore, the Kharif season starts from April–May and ends in September–October. The historical climatic data showed that May, June, July, and August are the hottest months in the Multan Region. The higher land surface temperature may also minor increase the evapotranspiration rate, hence increasing the irrigation water demand in the region (Basso et al., 2021). Evapotranspiration represents the climate of the region and can be used as decision support system to quantify the irrigation water demand (Ahsen et al., 2020; Kheir et al., 2021). In the Kharif season, canal water supplies were found to be maximum for cotton and rice crops due to its more planting area for these crops (Qureshi, 2020). The irrigation water supply ( $310.5 \text{ Mm}^3$ ) for the orchard was calculated annually which was further divided into both seasons

accordingly ( $157.6 \text{ Mm}^3$  in Rabi season and  $152.9 \text{ Mm}^3$  in Kharif season of year 2020). The other main source of water supply in the study area was rainfall. Rainfall was found to be a significant natural irrigation method in filling the gap between the demand and supply of water to crops (Al-Bakri et al., 2022).

The considerable gap between demand and supply for irrigation water ( $848.7 \text{ Mm}^3$ ) was found in Multan region due to change in planting area and decrease in canal water supply. The irrigation water demand and supply gap may affect the yield of the crop and crop water productivity (Foster et al., 2020; Janjua et al., 2021). The results of the study indicated that there is an urgent need for sustainable water management practices in the Multan region. The high demand for irrigation water and the widening gap between water supply and demand pose a significant challenge to the agricultural sector in the region and the overall country’s economy (An et al., 2021). To cover the demand and supply gap ( $848.7 \text{ Mm}^3$ ), the unsustainable groundwater extraction

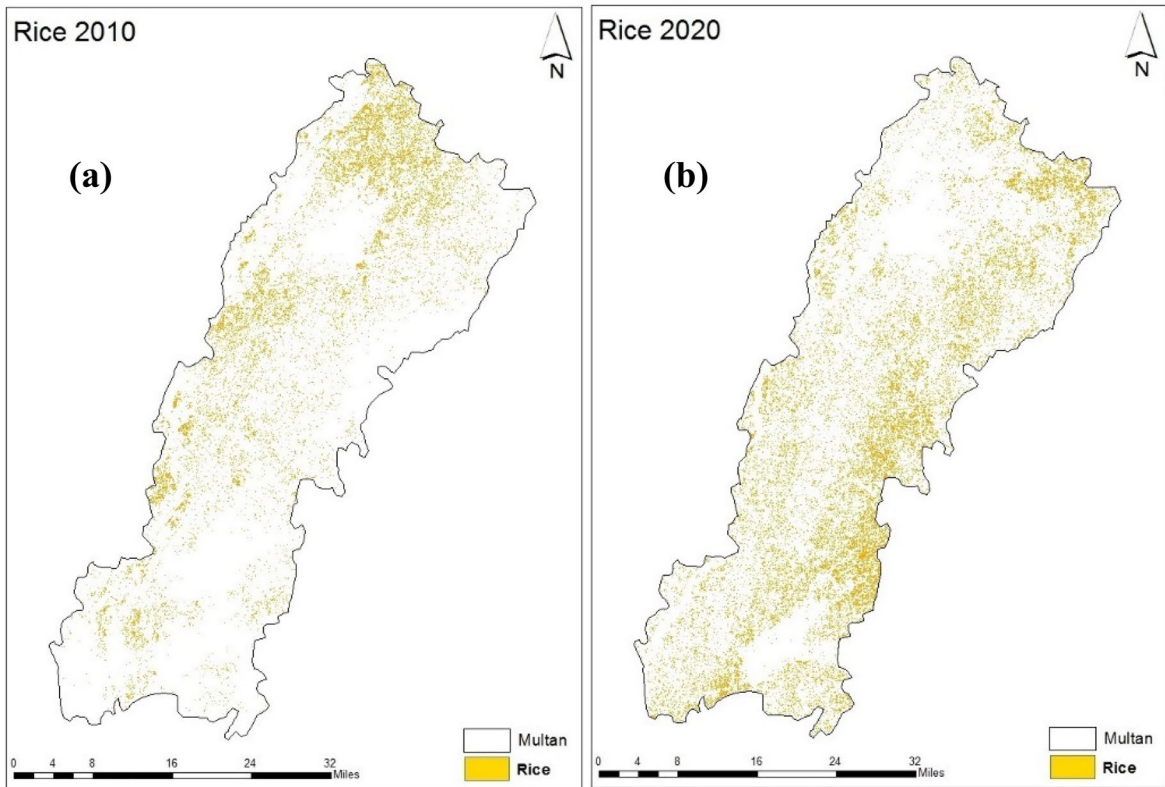


**Fig. 10** Land cover changes maps cotton Multan region (a) cotton crop in 2010, (b) cotton crop in 2020

is contributing to the depletion of groundwater resources. The challenge is more prominent in arid and semi-arid regions because these regions are relying on groundwater resources to support the irrigation system (Pradipta et al., 2022; Richey et al., 2015; Voss et al., 2013). The study found that the rate of groundwater extraction has increased significantly over the past few decades, leading to a declining water table (Mojid et al., 2019). The study estimates that the annual groundwater abstraction in Punjab is approximately 60 billion cubic meters, with the agricultural sector being the primary consumer, accounting for 97% of total groundwater abstraction. The overreliance on groundwater resources has also resulted in water quality issues, particularly in the areas where the water table is shallow, with increased salinity and contamination (Qureshi, 2020). The use of Landsat imagery,

irrigation supplies, and meteorological data provided accurate and reliable estimates of crop water requirements and actual water consumption by crops (An et al., 2021; Angella et al., 2016; Foster et al., 2020). The findings may help the farmers and water managers to make more informed decisions about equitable use of water in agriculture. The study also highlights the importance of improving irrigation efficiency to reduce water demand and bridge the supply gap. The results of this study also provide important insights into the current state of water resources in Multan region and highlight the potential of remote sensing and GIS technologies in addressing complex water-related issues (Lillo-Saavedra et al., 2021). The findings could inform policy decisions and help guide sustainable management practices and equitable distribution of water in the region and beyond.





**Fig. 11** Land cover changes maps for rice in Multan region (a) rice crop in2010, (b) rice crop in 2020

**Table 6** Accuracy assessment of LULC classification for 2010 and 2020

Sr no.	LULC class	Producer accuracy			User accuracy		
		2010	2020	Avg.	2010	2020	Avg.
1	Urban	84	86	85	91	88	89.5
2	Water Body	83.6	81	82.3	84.3	85	84.6
3	Orchards	82	83	82.5	75	89	82
4	Wheat	83	85.9	84.4	82.3	88	85.2
5	Sugarcane (Rabi)	79.1	80.1	79.6	80.4	83.7	82.1
6	Other crop (Rabi)	78.3	79.8	79.1	79.2	82.6	80.9
7	Cotton	82	81.4	81.7	83.5	86.7	85.1
8	Rice	81.9	82.6	82.2	84.8	87.5	86.2
9	Sugarcane (Kharif)	80.6	79.3	80	80.7	83.2	81.9
10	Other crop (Kharif)	83.2	81.6	82.4	81.4	79.5	80.4

**Conclusions**

The land use land cover (LULC) maps for years 2010 and 2020 were prepared for quantifying the demand and supply gap of irrigation water in Multan region, Pakistan using remote sensing and GIS

techniques. Accuracy assessment for the classified LULC map was performed using producer accuracy, user accuracy, and Kappa coefficient. The Kappa coefficient values (ranged from 0.78 to 0.85%) were found near to 1 indicated a substantial agreement between the classified maps and the ground truth

**Table 7** Overall accuracy and Kappa coefficient for Rabi and Kharif season

Year	Avg. producer accuracy	Avg. user accuracy	Overall accuracy	K	Avg. producer accuracy	Avg. user accuracy	Overall accuracy	K
Rabi Season				Kharif Season				
2010	84.6	85.3	84.9	0.78	84.2	81.8	83.8	0.83
2020	86.1	83.0	85.7	0.83	82.3	83.3	86.3	0.85
Average	85.3	84.1	85.3	0.8	83.2	82.5	85.1	0.84

**Table 8** Details of irrigation water demand in the study area from 2010 to 2020

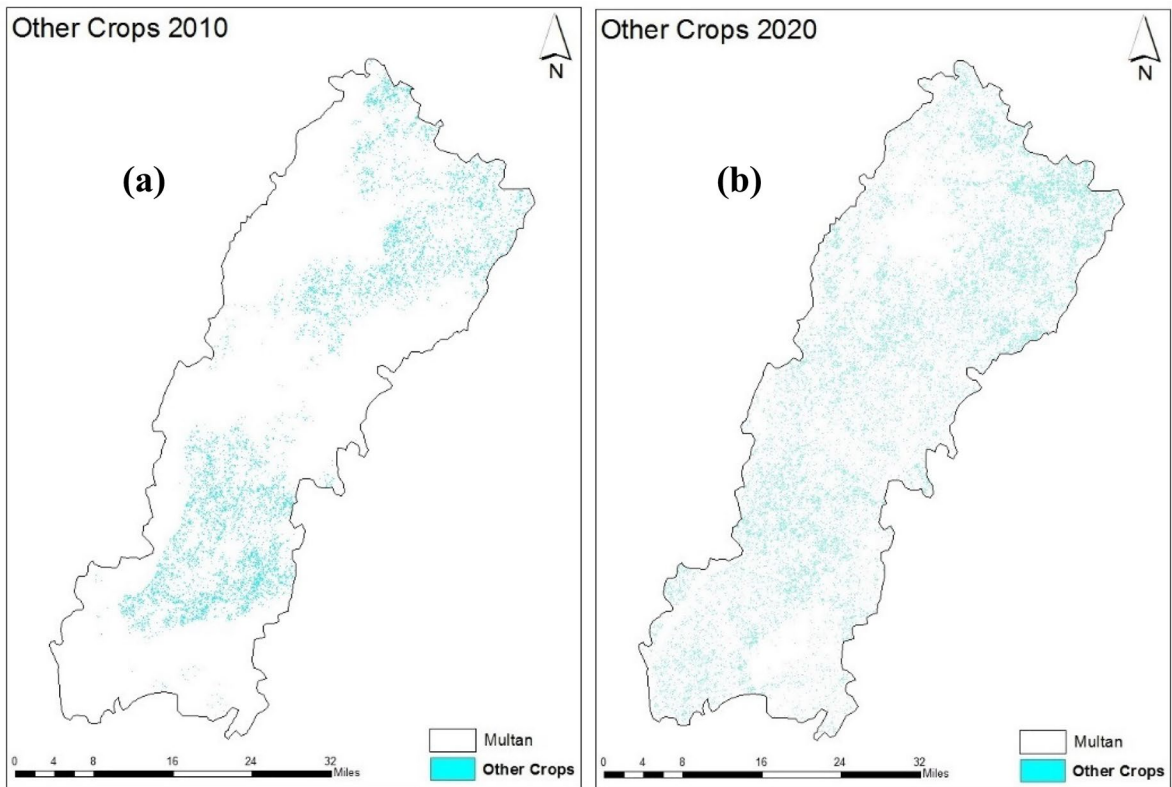
Crop	Irrigation water demand (Mm <sup>3</sup> )					
	2010		2020		2010-2020	
	Rabi	Kharif	Rabi	Kharif	Change	(%)
Wheat	852.2	-	781.5	-	-70.7	08 ↓
Rice	-	340.6	-	654.7	314.1	92 ↑
Cotton	-	1066.5	-	808.8	-257.7	24 ↓
Sugarcane	69.1	76.3	103.4	134.7	92.7	64 ↑
Other Crops	67.5	80.9	91.6	123	66.3	45 ↑
Orchards	511	587	263.7	319.3	-514.9	47 ↓
Total	1500	2150.9	1240.2	2040.5	-370.2	11 ↓
	3650.9		3280.7			

**Table 9** Seasonal canal water supply for the year of 2020

Crop	Seasonal canal water supply 2020 (Mm <sup>3</sup> )			Rainfall water supply 2020 (Mm <sup>3</sup> )		
	Rabi season	Kharif season	Annual	Rabi season	Kharif season	Annual
Wheat	221.4	-	221.4	255.3	-	255.3
Cotton	-	607.7	607.7	-	106.9	106.9
Rice	-	476.7	476.7	-	40.4	40.4
Sugarcane	63.4	86.4	149.8	19.7	7.1	26.8
Other Crops	28.6	72.2	100.8	36.7	24.8	61.5
Orchards	157.6	152.9	310.5	54.7	19.5	74.2
Total	471	1395.9	1866.9	366.4	198.7	565.1

**Table 10** Details of irrigation water demand/supply gap for the year of 2020.

Crops	Irrigation water demand/supply gap 2020 (Mm <sup>3</sup> )				
	Demand (Mm <sup>3</sup> )		Supply (Mm <sup>3</sup> )		Gap (Mm <sup>3</sup> )
	Irrigation water demand	Canal water supply	Rainfall water supply	Total supply	
Wheat	781.5	221.4	255.3	476.7	304.8
Cotton	808.8	607.7	106.9	714.6	94.2
Rice	654.7	476.7	40.4	517.1	137.6
Sugarcane	238.1	149.8	26.8	176.6	61.5
Other crops	214.6	100.8	61.5	162.3	52.3
Orchards	583	310.5	74.2	384.7	198.3
Total	3280.7	1866.9	565.1	2432	848.7

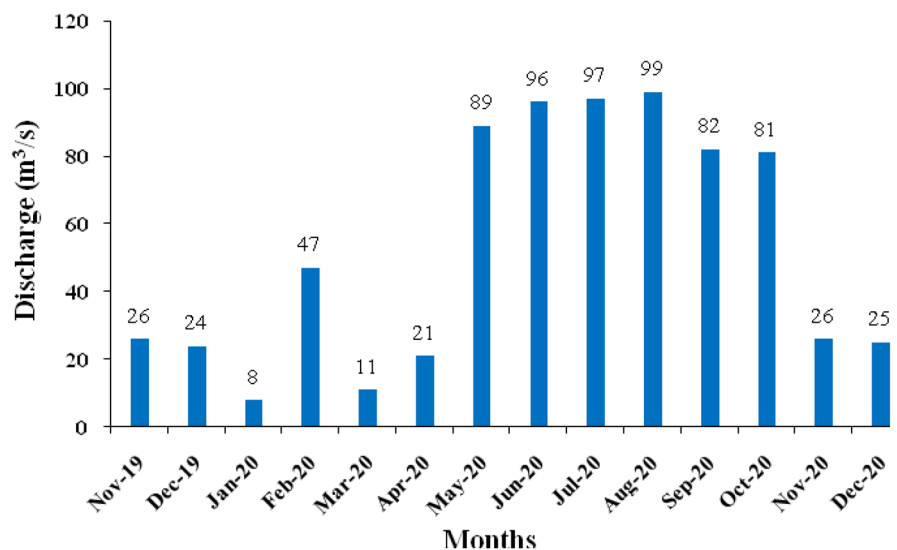


**Fig. 12** Land cover changes maps for other crops in Multan region (a) other crops in 2010, (b) other crops in 2020

data for both the years (2010 and 2020) and seasons (Rabi and Kharif). The LULC showed a consequential increase in urbanization of 49% from 2010 to

2020. The increase urbanization affected the overall vegetation and agricultural land use changes in Multan region. As result of increase in urban area,

**Fig. 13** Monthly canal water discharge variations in Multan region (2020)



the cropping pattern has changed from 2010 to 2020 which ultimately affects the irrigation water demand and supply in the region. About 304.8 Mm<sup>3</sup> demand and supply gap was observed for wheat which was due to the low relative canal water supply in the Rabi season. Orchards also showed a significant amount of demand and supply gap (198.3 Mm<sup>3</sup>) because orchards need water throughout the year. The total annual irrigation water demand for all the crops was found to be 3280.7 Mm<sup>3</sup>, and the total water supplied from (canals and rainfall) was 2432 Mm<sup>3</sup> without losses. The total demand and supply gap for the year 2020 has been quantified as 848.7 Mm<sup>3</sup> in the Multan region in 2020. These findings in terms of quantification of demand and supply gap provide the database for sustainable water management and equitable water distribution in the region. Results of this study also provide important insights to highlight the potential use of remote sensing and GIS technologies for water resource management. A future study should be formulated for the assessment of groundwater pumping to fill the irrigation water demand and supply gap for proper planning and management of groundwater resources.

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**Author contribution** All authors contributed to the study's conception and design. Data collection and analysis were performed by MH, HUF, MNA, AA, and MM. The first draft of the manuscript was written by MH, HUF, and ZMK. All authors read and approved the final manuscript.

**Data availability** Data will be made available from the corresponding author on reasonable request.

#### Declarations

**Ethical approval** All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

**Informed consent** There is no informed consent for this study.

**Conflict of interest** The authors declare no competing interests.

## References

- Ahmad, I., Ahmad, T., & Almanjahie, I. M. (2019). Modelling of extreme rainfall in Punjab: Pakistan using Bayesian and Frequentist approach. *Applied Ecology and Environmental Research*, *17*(6), 13729–13748. [https://doi.org/10.15666/aeer/1706\\_1372913748](https://doi.org/10.15666/aeer/1706_1372913748)
- Ahsen, R., Khan, Z. M., Farid, H. U., Shakoor, A., & Ali, I. (2020). Estimation of cropped area and irrigation water requirement using remote sensing and GIS. *Journal of Animal and Plant Sciences*, *30*(4), 876–884. <https://doi.org/10.36899/JAPS.2020.4.0103>
- Aik, D. H., Ismail, M. H., & Muharam, F. M. (2020). Land use/land cover changes and the relationship with land surface temperature using Landsat and MODIS imageries in Cameron drought Highlands, Malaysia. *Land*, *9*(10), 372. <https://doi.org/10.3390/land9100372>
- Akhtar, I. H., & Athar, H. (2020). Water supply and effective rainfall impacts on major crops across irrigated areas of Punjab, Pakistan. *Theoretical and Applied Climatology*, *142*(3–4), 1097–1116. <https://doi.org/10.1007/s00704-020-03337-7>
- Al-Bakri, J. T., D'Urso, G., Batchelor, C., Abukhalaf, M., Alobeiaat, A., Al-Khreisat, A., & Vallee, D. (2022). Remote sensing-based agricultural water accounting for the North Jordan Valley. *Water*, *14*(8), 1198. <https://doi.org/10.3390/w14081198>
- Almamalachy, Y. S., Al-Quraishi, A. M., & Moradkhani, H. (2020). Agricultural monitoring over Iraq utilizing MODIS products. In *Environmental Remote Sensing and GIS in Iraq 2020* (pp. 253–278). Springer, Cham. [https://doi.org/10.1007/978-3-030-21344-2\\_11](https://doi.org/10.1007/978-3-030-21344-2_11)
- An, M., Fan, L., Huang, J., Yang, W., Wu, H., Wang, X., et al. (2021). The gap of water supply—Demand and its driving factors: From water footprint view in Huaihe River Basin. *PLoS One*, *16*(3), e0247604. <https://doi.org/10.1371/journal.pone.0247604>
- Angella, G., García, V. M., López, J. M., Barraza, G., Salgado, R., Prieto, A. S., Tomsic, P., & Fereres, E. (2016). Quantifying yield and water productivity gaps in an irrigation district under rotational delivery schedule. *Irrigation Science*, *34*(1), 71–83. <https://doi.org/10.1007/s00271-015-0486-0>
- Arshad, A., Raza, M., Zhang, Y., Zhang, L., Wang, X., Ahmed, M., & Rahman, M. (2021). Impact of climate warming on cotton growth and yields in China and Pakistan: A regional perspective. *Agriculture*, *11*, 1–22. <https://doi.org/10.3390/agriculture-11020097>
- Basso, B., Martinez-Feria, R. A., Rill, L., & Ritchie, J. T. (2021). Contrasting long-term temperature trends reveal minor changes in projected potential evapotranspiration in the US Midwest. *Nature Communications*, *12*(1), 1476. <https://doi.org/10.1038/s41467-021-21763-7>
- Cutchan, M. M., Comber, A. J., Giannopoulos, I., & Canestrini, M. (2021). Semantic boosting: Enhancing deep learning based LULC classification. *Remote Sensing*, *13*(16), 1–24. <https://doi.org/10.3390/rs13163197>
- Ehlers, M., Greenlee, D., Smith, T., & Star, J. (1991). Integration of remote sensing and GIS: data and data access.

- Photogrammetric Engineering & Remote Sensing*, 57(6), 669–675.
- Foster, T., Mieno, T., & Brozovic, N. (2020). Satellite-based monitoring of irrigation water use: Assessing measurement errors and their implications for agricultural water management policy. *Water Resources Research*, 56, e2020WR028378. <https://doi.org/10.1029/2020WR028378>
- Fraiture, C., Molden, D., & Wichelns, D. (2010). Investing in water for food, ecosystems, and livelihoods: An overview of the comprehensive assessment of water management in agriculture. *Agricultural Water Management*, 97(4), 495–501. <https://doi.org/10.1016/j.agwat.2009.08.015>
- Hou, D., Meng, F., & Prishchepov, A. V. (2021). How is urbanization shaping agricultural land-use? Unraveling the nexus between farmland abandonment and urbanization in China. *Landscape & Urban Planning*. <https://doi.org/10.1016/j.landurbplan.2021.104170>
- Hussain, S., Mubeen, M., Ahmad, A., Akram, W., Hammad, H. M., Ali, M., Masood, N., Amin, A., Farid, H. U., Sultana, S. R., Fahad, S., Wang, D., & Nasim, W. (2020). Using GIS tools to detect the land use/land cover changes during forty years in Lodhran District of Pakistan. *Environmental Science and Pollution Research*, 27(32), 39676–39692. <https://doi.org/10.1007/s11356-019-06072-3>
- Jaiswal, R. K., Mukherjee, S., Krishnamurthy, J., & Saxena, R. (2003). Role of remote sensing and GIS techniques for generation of groundwater prospect zones towards rural development - An approach. *International Journal of Remote Sensing*, 24(5), 993–1008. <https://doi.org/10.1080/01431160210144543>
- Janjua, S., Hassan, I., Muhammad, S., Ahmed, S., & Ahmed, A. (2021). Water management in Pakistan's Indus basin: Challenges and opportunities. *Water Policy*, 23(6), 1329–1343. <https://doi.org/10.2166/wp.2021.068>
- Kafy, A. A., Bakshi, A., Saha, M., Al Faisal, A., Almulhim, A. I., Rahaman, Z. A., & Mohammad, P. (2023). Assessment and prediction of index based agricultural drought vulnerability using machine learning algorithms. *Science of The Total Environment*, 161394. <https://doi.org/10.1016/j.scitotenv.2023.161394>
- Kassawmar, T., Eckert, S., Hurni, K., Zeleke, G., & Hurni, H. (2018). Reducing landscape heterogeneity for improved land use and land cover (LULC) classification across the large and complex Ethiopian highlands. *Geocarto International*, 33(1), 53–69. <https://doi.org/10.1080/10106049.2016.1222637>
- Ke, Y., Im, J., Lee, J., Gong, H., & Ryu, Y. (2015). Characteristics of Landsat 8 OLI-derived NDVI by comparison with multiple satellite sensors and in-situ observations. *Remote Sensing of Environment*, 164, 298–313. <https://doi.org/10.1016/j.rse.2015.04.004>
- Khan, M., Hina, S., & Ali, H. (2019). Impact of urbanization on water resources of Pakistan: A review. *NUST Journal of Engineering Sciences*, 12(1), 1–8. <https://doi.org/10.24949/njes.v12i1.230>
- Khan, M. S., Ullah, S., Sun, T., Rehman, A. U., & Chen, L. (2020). Land-use/land-cover changes and its contribution to urban heat Island: A case study of Islamabad, Pakistan. *Sustainability (Switzerland)*, 12(9). <https://doi.org/10.3390/su12093861>
- Kheir, A. M., Alrajhi, A. A., Ghoneim, A. M., Ali, E. F., Magrashi, A., Zoghdan, M. G., et al. (2021). Modeling deficit irrigation-based evapotranspiration optimizes wheat yield and water productivity in arid regions. *Agricultural Water Management*, 256, 107122. <https://doi.org/10.1016/j.agwat.2021.107122>
- Kumar, M. G., Agarwal, A. K., & Bali, R. (2008). Delineation of potential sites for water harvesting structures using remote sensing and GIS. *Journal of the Indian Society of Remote Sensing*, 36(4), 323–334. <https://doi.org/10.1007/s12524-008-0033-z>
- Li, Y., Chen, Y., Duan, W., Cao, M., & Qin, J. (2022). Spatiotemporal variation in irrigation water requirements in the China–Pakistan economic corridor. *Scientific Reports*, 12(1), 17258. <https://doi.org/10.1038/s41598-022-21685-4>
- Lillo-Saavedra, M., Gavilán, V., García-Pedrero, A., Gonzalo-Martín, C., de la Hoz, F., Somos-Valenzuela, M., & Rivera, D. (2021). Ex post analysis of water supply demand in an agricultural basin by multi-source data integration. *Remote Sensing*, 13(11), 2022. <https://doi.org/10.3390/rs13112022>
- Mbungu, W. B. (2017). Impacts of land use and land cover changes, and climate variability on hydrology and soil erosion in the Upper Ruvu Watershed, Tanzania. [https://vtechworks.lib.vt.edu/bitstream/handle/10919/83863/Mbungu\\_WB\\_D\\_2017.pdf?sequence=1](https://vtechworks.lib.vt.edu/bitstream/handle/10919/83863/Mbungu_WB_D_2017.pdf?sequence=1)
- Mohsin, M., Mehmood, S., Jamal, F., & Answer, M. M. (2021). Modeling and forecasting of declining area and production of mango orchards in district Bahawalpur, Pakistan: A case of tehsil Ahmedpur East. *Journal of Agricultural Research*, 59(2), 197–212. [https://apply.jar.punjab.gov.pk/upload/1628067614\\_144\\_11\\_JAR\\_1543.pdf](https://apply.jar.punjab.gov.pk/upload/1628067614_144_11_JAR_1543.pdf)
- Mojid, M. A., Parvez, M. F., Mainuddin, M., & Hodgson, G. (2019). Water table trend—A sustainability status of groundwater development in North-West Bangladesh. *Water*, 11(6), 1182. <https://doi.org/10.3390/w11061182>
- Naeem, M., Farid, H. U., Madni, M. A., Ahsen, R., Khan, Z. M., Dilshad, A., & Shahzad, H. (2022). Remotely sensed image interpretation for assessment of land use land cover changes and settlement impact on allocated irrigation water in Multan, Pakistan. *Environmental Monitoring and Assessment*, 194(2), 98. <https://doi.org/10.1007/s10661-021-09732-5>
- Nguyen, T. T., Barber, P., Harper, R., Linh, T. V. K., & Dell, B. (2020). Vegetation trends associated with urban development: The role of golf courses. *PLoS One*, 15(2), e0228090. <https://doi.org/10.1371/journal.pone.0228090>
- Pradipta, A., Soupios, P., Kourgialas, N., Doula, M., Dokou, Z., Makkawi, M., et al. (2022). Remote sensing, geophysics, and modeling to support precision agriculture—Part 2: Irrigation management. *Water*, 14(7), 1157. <https://doi.org/10.3390/w14071157>
- Qureshi, A. S. (2020). Groundwater governance in Pakistan: From colossal development to neglected management. *Water*, 12(11), 3017. <https://doi.org/10.3390/w12113017>
- Richey, A. S., Thomas, B. F., Lo, M. H., Reager, J. T., Famiglietti, J. S., Voss, K., Swenson, S., & Rodell, M. (2015). Quantifying renewable groundwater stress with GRACE. *Water Resources Research*, 51, 5217–5237. <https://doi.org/10.1002/2015WR017349>
- Sajjad, A., Lu, J., Chen, X., Chisenga, C., Saleem, N., & Hassan, H. (2020). Operational monitoring and damage assessment

- of riverine flood-2014 in the lower Chenab plain, Punjab, Pakistan, using remote sensing and GIS techniques. *Remote Sensing*, 12(4), 714. <https://doi.org/10.3390/rs12040714>
- Salehi, M. (2022). Global water shortage and potable water safety; Today's concern and tomorrow's crisis. *Environment International*, 158, 106936. <https://doi.org/10.1016/j.envint.2021.106936>
- Salem, A., Abduljaleel, Y., Dezső, J., & Lóczy, D. (2023). Integrated assessment of the impact of land use changes on groundwater recharge and groundwater level in the Drava floodplain, Hungary. *Scientific Reports*, 13(1), 5061. <https://doi.org/10.1038/s41598-022-21259-4>
- Saleth, R. M., & Amarasinghe, U. A. (2010). Promoting irrigation demand management in India: Options, linkages, and strategy. *Water Policy*, 12(6), 832–850. <https://doi.org/10.2166/wp.2010.038>
- Shahbaz, B., & Ata, S. (2014). Enabling agricultural policies for benefiting smallholders in dairy, citrus and mango industries of Pakistan – Project No. ADP / 2010 / 091. 1–31.
- Shivakumar, B. R., & Rajashekararadhya, S. V. (2018). Investigation on land cover mapping capability of maximum likelihood classifier: A case study on North Canara, India. *Procedia Computer Science*, 143, 579–586. <https://doi.org/10.1016/j.procs.2018.10.434>
- Sidhu, R. S., Vatta, K., & Kaur, A. (2008). Dynamics of institutional agricultural credit and growth in Punjab: Contribution and demand-supply gap. *Agricultural Economics Research Review*, 21, 407–414 <http://ageconsearch.tind.io/bitstream/47891/2/12-RS-Sidhu.pdf>
- Silva, V. S., Salami, G., Silva, M. I. O., Silva, E. A., Monteiro, J. J., & Alba, E. (2020). Methodological evaluation of vegetation indexes in land use and land cover (LULC) classification. *Geology, Ecology, and Landscapes*, 4(2), 159–169. <https://doi.org/10.1080/24749508.2019.1608409>
- Tran, H. H., Van Tran, A., & Le, N. T. (2020). Study on land use changes, causes and impacts by remote sensing, GIS and Delphi methods in the coastal area of Ca Mau province in 30 years. *Journal of Mining and Earth Sciences*, 61(4), 36–45. [https://doi.org/10.46326/JMES.2020.61\(4\).04](https://doi.org/10.46326/JMES.2020.61(4).04)
- USDA. (2005). Irrigation Water Management: Chapter 9. Irrigation Guide, Part 652. [http://www.nespal.org/sirp/AWP/SCReport/NEH\\_Part\\_652\\_Chapter\\_09\\_Irrigation\\_Water\\_Management.pdf](http://www.nespal.org/sirp/AWP/SCReport/NEH_Part_652_Chapter_09_Irrigation_Water_Management.pdf)
- Vanbelle, S., & Albert, A. (2008). A bootstrap method for comparing correlated kappa coefficients. *Journal of Statistical Computation and Simulation*, 78(11), 1009–1015. <https://doi.org/10.1080/00949650701410249>
- Vivekananda, G. N., Swathi, R., & Sujith, A. V. L. N. (2021). Multi-temporal image analysis for LULC classification and change detection. *European Journal of Remote Sensing*, 54(sup2), 189–199. <https://doi.org/10.1080/22797254.2020.1771215>
- Voss, K. A., Famiglietti, J. S., Lo, M., de Linage, C., Rodell, M., & Swenson, S. C. (2013). Groundwater depletion in the Middle East from GRACE with implications for transboundary water management in the Tigris-Euphrates-Western Iran region. *Water Resources Research*, 49, 904–914. <https://doi.org/10.1002/wrcr.20078>
- Wrzesiński, D., & Sobkowiak, L. (2020). Transformation of the flow regime of a large allochthonous river in Central Europe—An example of the vistula river in Poland. *Water*, 12(2), 507. <https://doi.org/10.3390/w12020507>
- Zappa, L., Schläffer, S., Bauer-Marschallinger, B., Nendel, C., Zimmerman, B., & Dorigo, W. (2021). Detection and quantification of irrigation water amounts at 500 m using sentinel-1 surface soil moisture. *Remote Sensing*, 13(9), 1727. <https://doi.org/10.3390/rs13091727>
- Zhang, D., Sial, M. S., Ahmad, N., Filipe, J. A., Thu, P. A., Zia-Ud-din, M., & Caleiro, A. B. (2021). Water scarcity and sustainability in an emerging economy: A management perspective for future. *Sustainability (Switzerland)*, 13(1), 1–10. <https://doi.org/10.3390/su13010144>
- Zhu, Z., & Dou, J. (2018). Current status of reclaimed water in China: An overview. *Journal of Water Reuse and Desalination*, 8, 293–307. <https://doi.org/10.2166/WRD.2018.070>

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