RESEARCH PAPER

INDEX-BASED SPATIOTEMPORAL ASSESMENT OF WATER QUALITY IN TARBELA RESERVOIR, PAKISTAN (1990–2020)

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ABSTRACT. Anthropogenic activities can greatly influence the lake ecosystems across the globe. Within these ecosystems, the impacts of human activities are most evident on sedimentation, light and nutrient availability, and disturbance frequency. There have been times of natural environmental healing of reservoirs and the present research aims to explore the variations in the water quality of Tarbela reservoir, Pakistan the largest rock-filled dam of the world, from 1990 to 2020. Landsat imagery (Landsat 4-5, 5, 7 and 8) was used to monitor Land Use Land Cover (LULC), Normalized Difference Chlorophyll Index (NDCI), Normalized Difference Turbidity Index (NDTI) and Normalized Difference Water Index (NDWI) in Tarbela reservoir, and its surrounding area from 1990–2020, on decadal interval. The results indicated a significant increase in built-up area, of about 630 km^2, in the western and eastern parts of the reservoir, whereas turbidity level, revealed a substantial decline with 4% decrease observed in the last decade, 2010-2020 thus confirming improved water quality. The study also presented expanse in the spatial coverage of chlorophyll index and water index, indicating increase in residence time of the water. It is concluded that the water quality continued to deteriorate with time, however, 2020 was a year of environmental healing and there was an overall water quality improvement of the reservoir observed. The study recommends policies to be formulated for sediment flushing and turbidity reduction for longer time duration to enhance the life of this mega reservoir.

KEYWORDS: Chlorophyll, Turbidity, Water Index, Landsat, Tarbela

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INTRODUCTION

Reservoir construction, as an anthropogenic activity continue to alter and influence fluvial processes, including sediment transportation, its resultant altered river geomorphology, geochemical composition of water and ecology (Pogorelov et al. 2021, Condé et al. 2019). The uncontrolled population increase, along with climatic variability, leads to intensive land use practices that impact the water level and clarity of water in inland water reservoirs. A risk assessment approach, in this context, can highlight the magnitude of damage they cause to the lacustrine environment (Ochoa-Contreras et al. 2021; Lymburner et al. 2016).

Inland reservoirs retain the increased sediment and nutrient fluxes, which are induced due to intensified land use practices and human induced disturbances in watershed area, which lead to the eutrophication and degradation of water quality and basin-scale hydrological regimes (Harrison et al. 2010; Lymburner et al. 2016; Zhang et al. 2021). Human induced sediment and nutrient fluxes function as pollutant stressor and impact biodiversity and human consumption (Vörösmarty et al. 2010). Similarly, anthropogenic activities in coastal areas have been said to be responsible for enhanced turbidity in coastal waters (Dorji and Fearns 2017). Land use/land cover change (LULCC), transformation is being experienced in and around growing towns (Amin et al. 2014). In recent decades, the developing countries have witnessed water pollution after unprecedented population growth and industrialization (Singh et al. 2016). Thus, there remains a need for water quality assessment in inland waters by measuring the concentration of human-induced pollutants that degrade the aquatic ecosystem in any water reservoir (Hegazy et al. 2020; Poletaeva et al. 2021).

Inland waters are sensitive to anthropogenic activities and have been affected by environmental disturbances resulting from these anthropogenic activities, which affect both water quality and hydrological characteristics, which explains the demand for assessing and monitoring water quality parameters (Koronkevich et al. 2019). The present climate change and anthropogenic activities like industrial expansion, urban development, and agricultural practices and natural processes such as precipitation frequency, weathering processes, and transportation of sediments, collectively add sediment flow to reservoirs that affect the water quality and storage capacity of the reservoir simultaneously (Das 2021). Similarly, a recent study pointed out that afforestation schemes like Billion Tree Afforestation Project (BTAP) can decrease the sediment load generation in the catchment area of Tarbela reservoir (Shafeeque et al. 2022).

To study sediment concentration and turbidity level in reservoirs, remotely sensed data is of vital importance for quantification of both variables (Wu et al. 2007; Dorji and Fearns 2017). Turbidity is an important water quality parameter from its optical property perspective. It varies spatio-temporally over large waterbodies. Normalized Difference Turbidity Index (NDTI) for example, has been used for qualitative estimates of turbidity in inland waterbodies around the globe (Garg et al. 2017). Remotely sensed images can assess the dredging impacts on water turbidity (Wu et al. 2007), similarly flat-bed pattern in the lower part of reservoirs can be detected through turbidity currents (Petkovšek 2018). Sedimentation trends and turbidity levels in reservoirs are highly determined by human settlements constructed near them. These settlements add loads of fine suspended sediments to the nearest water body which further accumulate in the bottom of the reservoir and create "muddy water" (Rutherfurd et al. 2020). Sediments from any natural or human source not only decline the water quality of the reservoir but also its water storage efficiency and also lead to other disasters (Petkovšek 2018, Tundu et al. 2018).

Elevated chlorophyll-a (pigment found in all phytoplankton species) concentrations generally indicate a change in the trophic status of a water body, and it is mainly associated with degraded water quality and low biodiversity which adversely destabilizes the ecosystem services and functions (Dalu et al. 2015; Kudela et al. 2015; Masocha et al. 2018). The understanding of the chlorophyll-a spatio-temporal dynamics requires frequent monitoring for water quality management (Andrade 2019). Chlorophyll-a, which is detectable by satellite imagery, therefore, can serve as an indicator of the presence of an algal bloom and is our liable source for water quality (Mishra & Mishra 2012). Various bio-optical algorithms have been designed to retrieve the chlorophyll-a concentration in inland waters, adopting different band combinations. One of the most abundant photo pigments produced by all types of algae is Normalized Difference Chlorophyll Index (NDCI) algorithm (Johansen et al. 2018; Mishra & Mishra 2012). The residence time of water in the reservoirs indirectly leads to eutrophication, as the nutrients get time to stay in water for longer periods (Calijuri et al. 2002). Although eutrophication is a natural phenomenon, however human activities such as, discharge of industrial, agricultural, or domestic effluents, can lead to cultural eutrophication (Rabalais et al. 2009; Bhagowati & Ahamad 2019; Çelekli 2020). The existence of phytoplankton in the in aquatic system, is indicative of enhanced primary productivity (Cai et al. 2011) and leads to high emission of greenhouse gases (Giles 2006; Barros et al. 2011). Being a photosynthetically active pigment, chlorophyll can be used for the determination of phytoplankton biomass (Watanabe et al. 2015).

As novel Coronavirus pandemic hit the world at the end of 2019, there was a halt to major human-induced events due to lockdown and as a result, the natural environment has experienced many changes (Xu et al. 2020). The current study is looking towards the impact of COVID-19 lockdown on the water quality of reservoirs. Globally many rivers, coastal waters and reservoirs examined a profound change in water quality from a positive perspective. Most anthropogenic activities were stopped and inclusion of all pollutants to water channels was declined and most reservoirs regained their clean waters (Dutta et al. 2020; Robin et al. 2021, Arakelov et al. 2021).

Studies have been conducted in past exploring the reservoir sedimentation (Tate and Farquharson 2000; Khan and Tingsanchali 2009; Roca 2012; Mazhar et al. 2021), while others dealt with floor risk assessment (Naz et al. 2019), operational changes in the reservoir (Rafique et al. 2020) and a study even investigated the physiochemical water quality of Tarbela near the federal capital, Islamabad (Ahmed et al. 2015). Although studies have been conducted to spatially monitor the water quality of reservoirs, using remote sensing technology (González-Márquez et al. 2018, Vakili and Amanollahi 2020), however, there has been a gap in terms of assessing this water quality over longer time scales, and the present research aims to fill this gap by exploring the variations in the water quality of Tarbela reservoir for the last 30 years. The study fundamentally has the following objectives: i) to monitor the water quality of Tarbela reservoir from 1990–2020, using remotely sensed data and ii) to explore any changes in the water quality of the reservoir in period under study.

MATERIALS AND METHODS

Study area

Tarbela reservoir, situated in Haripur and Swabi district in Pakistan, about 50 km northwest of Islamabad (Ahmed et al. 2015), is the earth's largest rock filled dam, constructed over River Indus in 1976 (Mazhar et al. 2021). At the time of conception, its main functions were power generation and regulation of seasonal flows for irrigating the Indus plains (Roca 2012). The reservoir had an initial capacity of 11, 600 m^3 (Roca 2012). According to Tate and Farquharson (2000), average daily temperature varies substantially from -7º C in January to 41º C in June, while the relative humidity normally remains low, but more than 50% humidity is witnessed only in pre-monsoon period. The average annual rainfall at Tarbela is around 899 mm, scattered in almost all the months of the year. January and November rarely go rainless. The average inflow in the reservoir is 81, 000 Mcm as shared in TAMS 1998 report (Roca 2012), while Tate and Farquharson (2000) state that snowmelt plays a significant role in raising the peak flows of the reservoir, with snowmelt contributing peak flows as high as 11, 300 m^3s^{-1}, comparatively, rainfall contributes a maximum of 5, 660 m^3s^{-1}.

The geographical coordinates of the reservoir are 34.1438° North latitude and 72.8077° East longitude (Fig. 1). The mean rainfall recorded at Tarbela was 74.41mm for the period 1960-1996 (Tate and Farquharson 2000).

DATA ACQUISITION

The characteristics of Landsat data used in the study are provided in Table 1.

PREPROCESSING

The above-mentioned data was acquired from United States Geological Survey (USGS). Preprocessed Landsat imagery from1990 to 2020 was downloaded from USGS. Preprocessing of data included geometric and radiometric correction, noise removal and cloud cover which was less than 10%. Later, Earth Resources Data Analysis

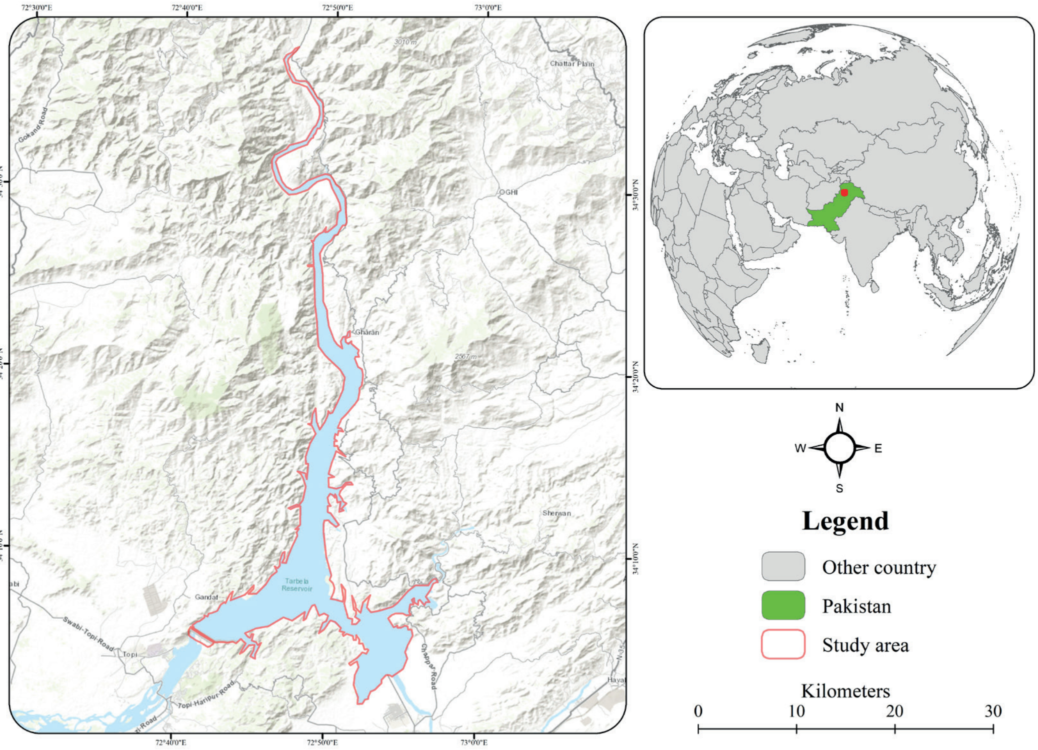

Fig. 1. Study Area Map

Table 1. Characteristics of Landsat data used in the study

Satellite	Sensor	Level	Path	Row	Acquisition Date
Landsat 5	TM	L1	150	36	1990/04/24
Landsat 5	TM	L1	150	36	2000/05/21
Landsat 7	ETM+	L1	150	36	2010/06/02
Landsat 8	OLI	L1	150	36	2020/06/29

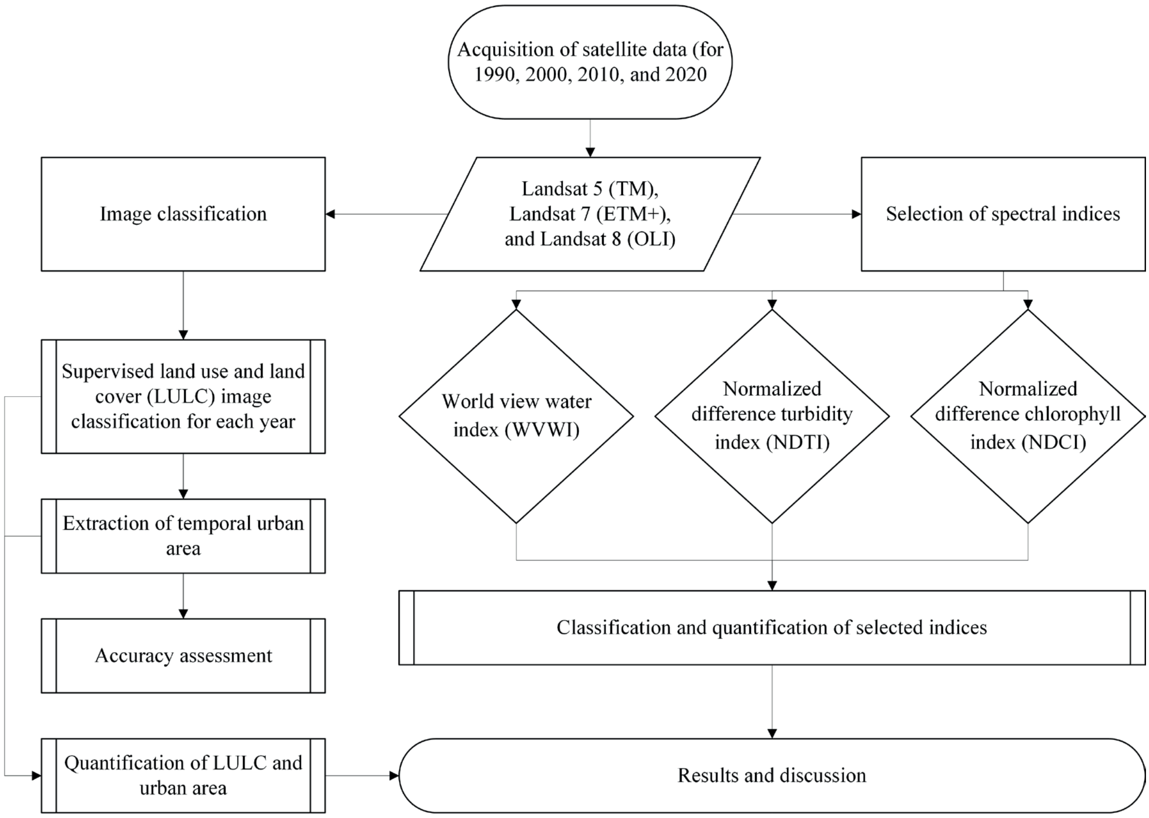

Fig. 2. Methodological Flow chart

System (ERDAS) Imagine was used for layer stacking and mosaicking of images.

Land use land cover classification (LULC)

Land use/land cover change (LULCC) quantification is one of the important applications of earth observation data sets, and it is vital for assessing global environmental change processes and helps in optimizing the maximum use of natural resources in sustainable manner and making new policies (Srivastava et al. 2012; Singh et al. 2016). LULC changes due to afforestation programs also need to be monitored closely through remotely sensed data, as sediment generation rate is impacted by different land uses (Shafeeque et al. 2022). Supervised classification with maximum likelihood algorithm was applied on the Landsat imagery for land use land cover analysis. The study area was broadly classified into five classes, somewhat similar to USGS Level 1 classification scheme (Radhakrishnan 2014; Singh et al. 2016). The waterbody class included all the areas covered by water, including rivers, reservoir, streams, lakes, and ponds: vegetation class included all the sparse forest vegetation and also grass, crops, parks etc. The snow class covered all the pixels showing the presence of snow/ ice; the boulder/rocks class covered all the land covered by boulders and rocks within the reservoir boundary and the concrete structures outside the reservoir boundary. The bareland class included the areas without sparse vegetation, without boulders.

To identify the errors, accuracy evaluation is an essential step of image processing procedures (Alam et al. 2019; Hussain et al. 2021; Kumar et al. 2021 & Hussain & Karuppannan 2022). Overall accuracy determines the correctness of the classification process (Mukherjee & Singh 2020; Mishra & Jabin 2020). In order to calculate the accuracy of each class of LULC from LANDSAT images, an accuracy assessment was performed in ArcGIS using the equation 1:

$$= \frac{Total\ Number\ of\ Correct\ Classify\ Pixels\ (Diagonal)}{Total\ Number\ of\ Reference\ Pixels} * 100 \quad (1)$$

Producer's accuracy quantitatively exhibits if all attributes shown in real map are correctly classified (Mukherjee & Singh 2020, Singh & Jabin 2020, Kafy et al. 2021). The Producer Accuracy was calculated through equation 2:

$$= \frac{Number\ of\ Correct\ Classify\ Pixels\ in\ Each\ Category}{Total\ Number\ of\ Reference\ Pixels\ in\ that\ Category\ (The\ Column\ Total)} * 100 \quad (2)$$

In addition, Kappa coefficient measures accuracies between two random values and show reasonable accuracy. Kappa coefficient is regarded as a coefficient of agreement (Mukherjee & Singh 2020; Mishra & Jabin 2020; Gondwe et al. 2021; Bunyangha et al. 2021). The Kappa Coefficient was calculated using equation 3:

$$= \frac{(TS * TCS) - \Sigma(Column\ Total * Row\ Total)}{TS^2 - \Sigma(Column\ Total * Row\ Total)} * 100 \quad (3)$$

According to the assessment results, the overall accuracy of 1990 image was 91.43% with a Kappa coefficient value of 0.89, while the overall accuracy of 2000 image was 90.91% with a Kappa coefficient value of 0.89; the overall accuracy of 2010 image was 86.67% with a Kappa coefficient value of 0.83 and the overall accuracy of 2020 image was 88% with a Kappa coefficient value of 0.85 (table 2).

WORLD VIEW WATER INDEX (WVWI)

World View Water Index (WVWI) has been reported to be a powerful algorithm that detects water or shadows (IMAGINE 2015). This index works with coastal and Near Infrared Reflectance (NIR2) bands, as both these bands have variation in wavelengths, therefore, it provides a reliable threshold to identify water (Wolf 2012) using equation 4.

$$WVWI = \frac{CB - NIR2}{CB + NIR2} \quad (4)$$

NORMALIZED DIFFERENCE TURBIDITY INDEX (NDTI)

The turbidity in inland waters, like ponds and reservoirs, can be monitored through remotely sensed images (equation 5), using the NDTI developed by Lacaux, Tourre et al. (2007).

$$NDTI = \frac{Red - Green}{Red + Green} \quad (5)$$

Moderate Resolution Imaging Spectroradiometer (MODIS) data can also be used to monitor water surface turbidity at both the reservoir level, by analyzing the turbidity pattern variability in each reservoir, and the sedimentation pattern at the water surface can also be retrieved (Condé et al. 2019).

Table 2. Accuracy assessment (%)

Year	1990		2000		2010		2020	
Accuracy	User (%)	Producer (%)	User (%)	Producer (%)	User (%)	Producer (%)	User (%)	Producer (%)
Landcover								
Water	87.5	100	100	100	91.67	68.75	100	83
Vegetation	100	83.33	92.31	85.71	82.35	82.35	90	90
Snow	100	100	100	100	81.81	100	75	100
Boulder/Rock	66.67	100	83.33	90.91	88.89	100	91.66	84.61
Bare Land	100	85.71	80	80	90.9	100	80	88.89
Overall Accuracy (%)	91.43		90.91		86.67		88.00	
Kappa Coefficient	0.89		0.89		0.83		0.85	

NORMALIZED DIFFERENCE CHLOROPHYLL INDEX (NDCI)

Phytoplankton has been used as an organism that is indicative of health of a water body, while phytoplankton cannot exist without chlorophyll. Chlorophyll content in water bodies can be traced through NDCI (equation 6), which can help trace algae growth (Mishra, Schaeffer et al. 2014). It is necessary to monitor chlorophyll content in reservoirs because excessive growth of phytoplankton can lead to eutrophication, thus affecting the efficiency of the reservoir for power generation and provision of irrigation water.

$$NDCI = \frac{Blue}{Red} \qquad (6)$$

In order to monitor the settlement expanse during the years under study, Google earth high resolution images were georeferenced and later stretch option of symbology was applied on these images, using Arc GIS 10.3.

RESULTS

LAND USE AND LAND COVER (LULC)

The analysis of Fig. 3 presents the interesting finding that the water class underwent increase in area from 167 km^2 in 1990 to 196 km^2 in 2020, with maximum increase witnessed on the eastern banks of the reservoir. However, the bare land class witnessed the greatest decrease of 3184 km^2 during the period under study. The bare land area was maximum in the year 1990, after which it steadily declined, so much so, that its area was merely 549 km^2 in 2020 (table 3). The bare land area was replaced by vegetation, as this class also underwent massive increase of 2593 km^2 from 1990 to 2020.

Similarly, the boulders/rocks class, also representing the settlement area in the area of interest, experienced a substantial increase of 609 km^2. The snow-covered class existed only in year 1990 and 2010, and its spatial coverage remained less than 50 km^2 and that too limited to only north eastern side of the study area.

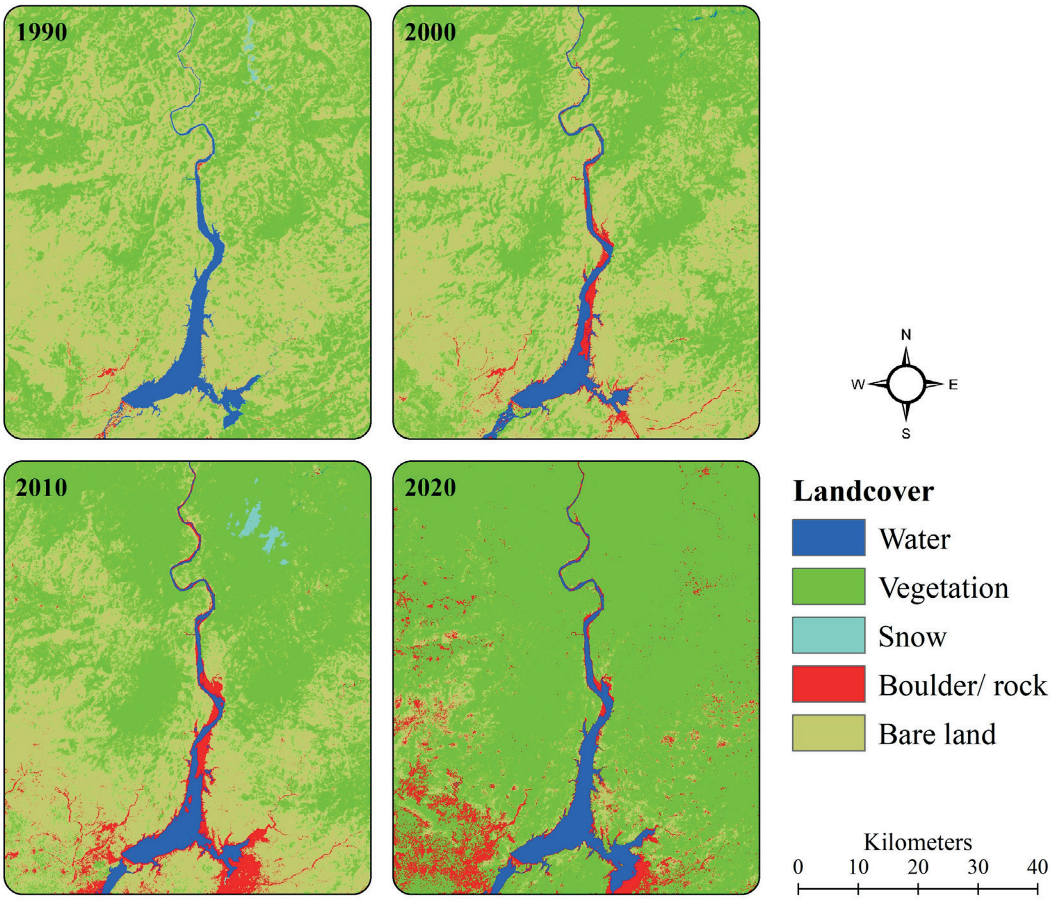

Fig. 3. LULC classification of Tarbela reservoir, 1990–2020

Table 3. Land Use and Land Cover (LULC) characteristics of the study area

Classes	1990 area (sq.km)	2000 area (sq.km)	2010 area (sq.km)	2020 area (sq.km)
Water	167	166	151	196
Bare Land	3733	3424	2680	549
Boulders/Rock	20	90	321	630
Snow	47	0	44	0
Vegetation	2100.94	2388	2872	4694

NORMALIZED DIFFERENCE CHLOROPHYLL INDEX (NDCI)

Figure 4 presents the spatio-temporal variations in the chlorophyll level of the study area. The high NDCI class underwent a decrease of 712%, while the low class of NDCI experienced a decrease of 33%.

The highest NDCI value was recorded in 1990, while the lowest high value of NDCI was identified in 2020. The mean values of NDCI indicate a gradual decrease in the intensification of NDCI from 3.04 in 1990 to 1.12 in 2020 (table 4). Another significant finding is that although the intensity of the high NDCI decreased over the years, however, its spatial coverage significantly increased by 2020. The eastern and western arms of the reservoir, located in the south of the study area appear saturated with high chlorophyll content. This increase in spatial coverage of NDCI shows high eutrophic activity which affects the water quality (Watanabe, Alcântara et al. 2015; Liu, Zhang et al. 2019).

NORMALIZED DIFFERENCE TURBIDITY INDEX (NDTI)

Figure 5 presents the turbidity variation in Tarbela reservoir and its surrounding area. The area covered by high turbidity has declined from 0.15 to 0.09 from 1990 to 2020 (see Table 5) and witnessed a total decrease in spatial coverage by 6%. Whereas there was an increase of 16% recorded for the low NDTI class, which points towards the environmental healing, where the turbidity significantly declined over the years leading to cleaner water concentration in the left and right arm of the reservoir in 2020. The highest spatial coverage of low NDTI was in 2000, while the lowest was observed in the year 1990. However, the mean value of NDTI has increased from -0.13 in 1990 to -0.05 in 2020, which proves gradual decrease in the turbidity level of the waters of the Tarbela reservoir, over the years.

WORLD VIEW WATER INDEX (WVWI)

According to Fig. 6, the spatial extent of water has increased in Tarbela reservoir over the years,

Table 6. World View Water Index (WVWI) characteristics of the study area precisely in year 2020, representing second most widespread spatial coverage of WVWI, after 1990. However, according to Table 4, the highest value of WVWI has decreased by 44% over the years, with highest value of 0.80 recorded in 2000, and lowest value of high WVWI of 0.34 reported in 2020 (Table 6). Similarly, the low WVWI class underwent a 28% decrease from -0.29 in 1990 to -0.57 in 2020. The mean WVWI has also witnessed a decline from 0.13 in 1990 to -0.11 in 2020, thus referring to an overall decrease in intensification of the WVWI values.

SETTLEMENT EXPANSE

Settlement expanse in the study area can be identified through Fig. 7, where shades of brown are indicative of settlement expansion. The same can be seen to be increasing steadily in the south eastern and south western parts of the study area. The rapid expanse of these settlements on the banks of the reservoir hint towards human intervention in the water quality of the reservoir.

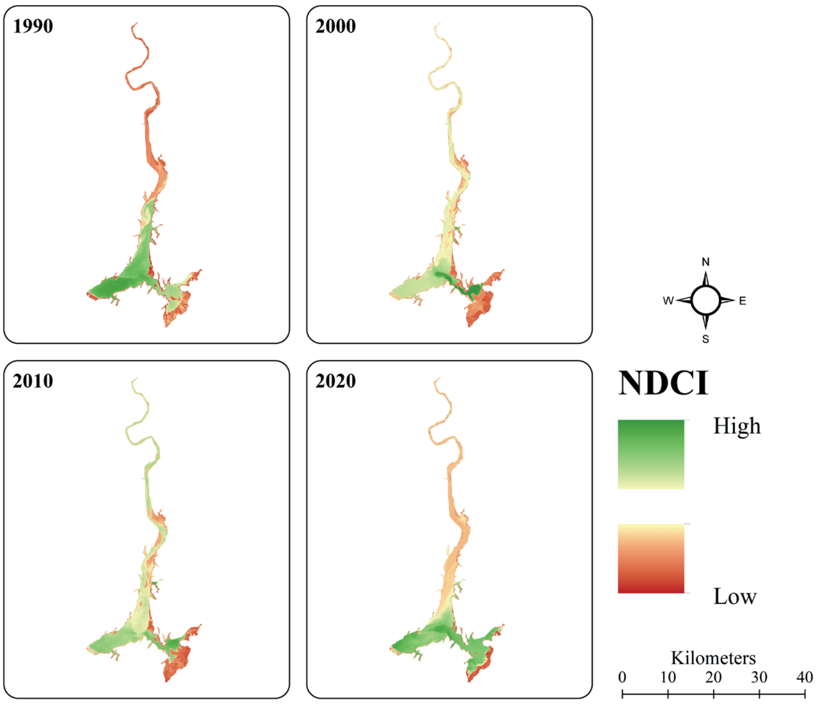

Fig. 4. NDCI of Tarbela reservoir, 1990–2020

Table 4. Normalized Difference Chlorophyll Index (NDCI) characteristics of the study area

Classes	1990	2000	2010	2020
High	4.80	3.04	2.49	1.35
Medium	2.99	2.04	1.86	1.05
Low	1.19	1.05	1.24	0.75
Mean	3.04	1.76	1.79	1.12

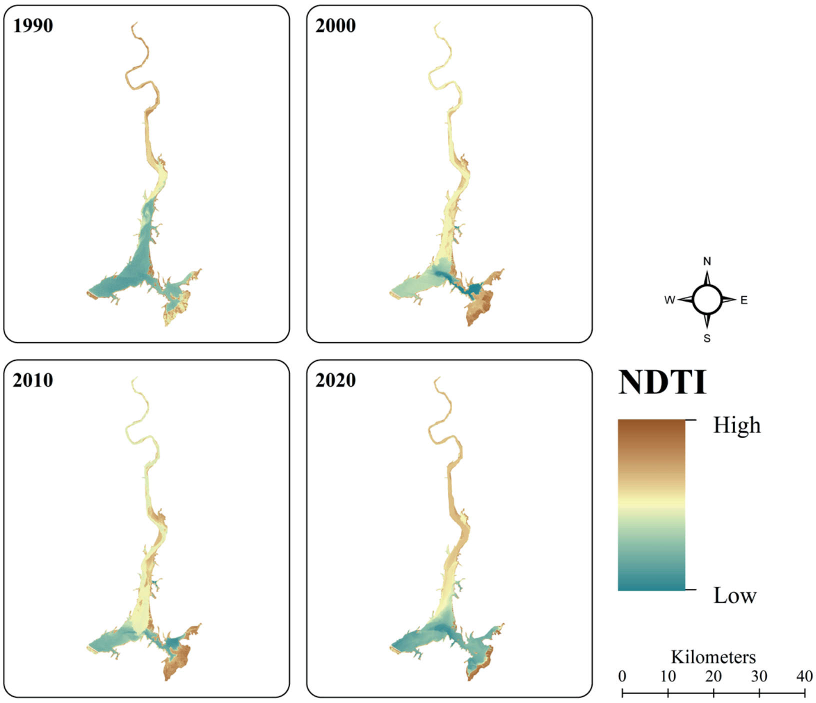

Fig. 5. NDTI of Tarbela reservoir, 1990–2020

Table 5. Normalized Difference Turbidity Index (NDTI) characteristics of the study area

Classes	1990	2000	2010	2020
High	0.15	0.21	0.17	0.09
Medium	-0.07	0.01	0.04	-0.02
Low	-0.30	-0.18	-0.08	-0.14
Mean	-0.13	0.05	0.05	-0.05

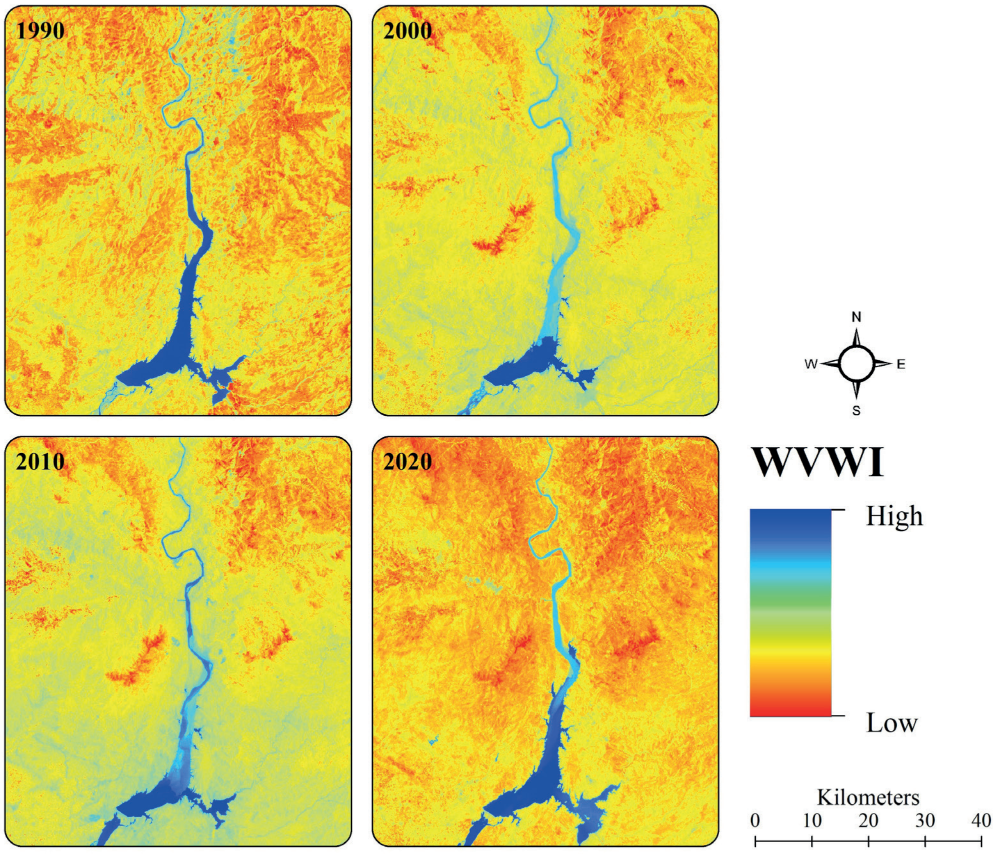

Fig. 6. WVWI of Tarbela reservoir, 1990–2020

Table 6. World View Water Index (WVWI) characteristics of the study area

Classes	1990	2000	2010	2020
High	0.78	0.80	0.63	0.34
Medium	0.17	0.07	0.11	-0.21
Low	-0.11	-0.23	-0.13	-0.46
Mean	0.13	0.28	0.21	0.20

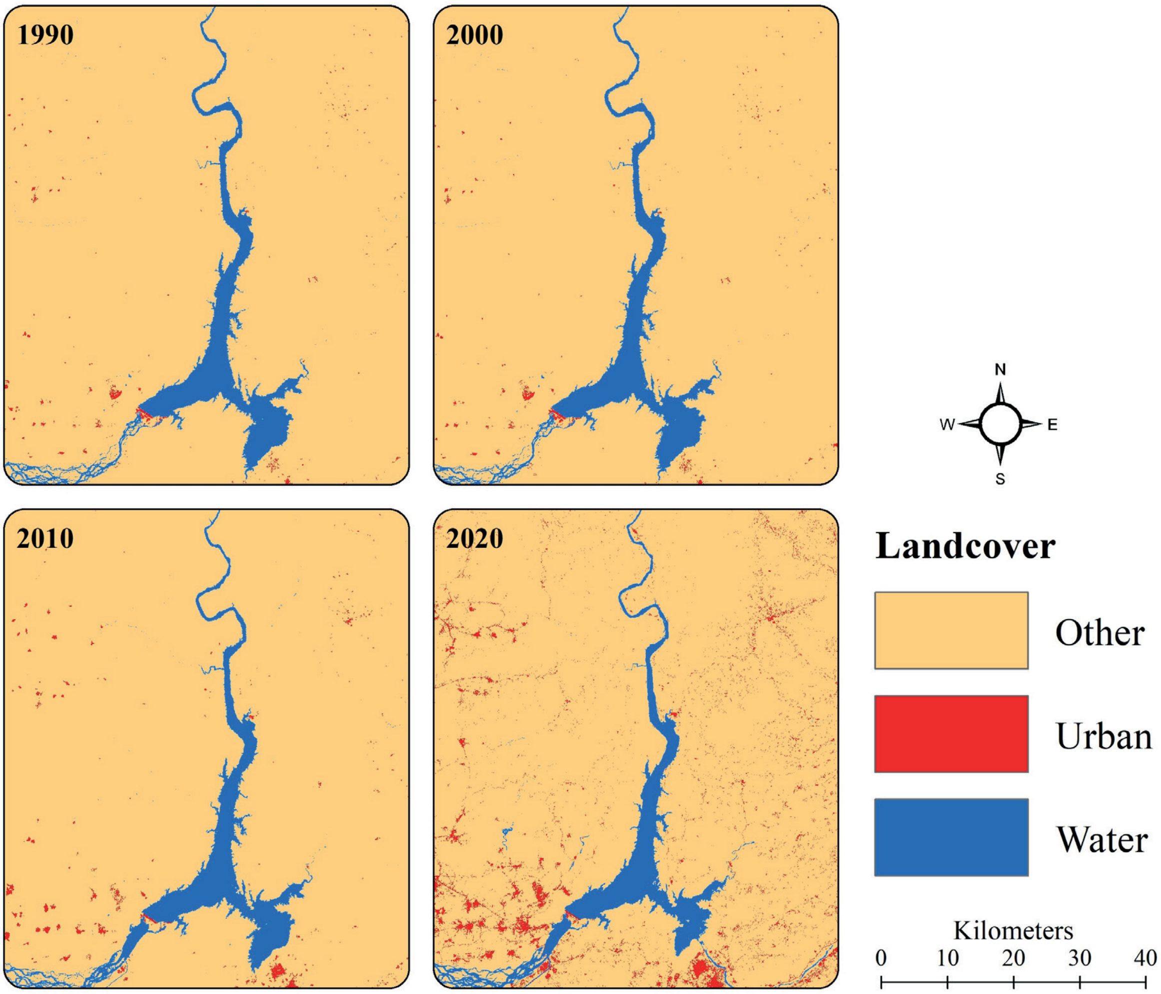

Fig. 6. WVWI of Tarbela reservoir, 1990–2020

DISCUSSION

This study explored the water quality of world's largest earth and rock filled dam, and its surroundings, using geospatial techniques. The results indicated significant increase in built-up area, of about 609 km^2, in the western and eastern parts of the reservoir, from 1990 to 2020. This increase in built up, corresponds with decrease in bare land and increase in vegetation cover over the years and all these directly have impacts on water quality as Srivastava et al. (2012) have mentioned that the combination with remote sensing water quality, the use of multivariate statistical techniques offers a detailed understanding of water quality parameters and possible factors that influence the water quality behavior. The findings of this study can be supported by another recent study where the expanse in vegetation has been reported in the catchment and area around Tarbela reservoir, due to the BTAP project (Shafeeque et al. 2022).

From 1990 to 2010, within the reservoir boundary substantial increase in the boulder class can be identified which is supported by the notion that during the pre-lockdown years, the water drawdown was high from Tarbela for agricultural and hydroelectric power generation purposes, which resulted in the exposure of the boulders lying along the reservoir edges, when the waterlevel went too low. However, in 2020, after Covid-19 related lockdown in Pakistan, an increase in the water level within the reservoir was witnessed which led to the submergence of the boulders within the reservoir boundary. However, an increase in the same category was identified on the south western bank of the reservoir, during the same period, which can be associated with settlement expanse in the region. The Landsat data comparison presents the variation in turbidity, chlorophyll and water area during pre-Covid-19 years and Covid-19 year.

The analysis of the water quality based on turbidity level, revealed a substantial decline in turbidity of the reservoir with 4% decrease observed in the last decade, thus hinting towards the higher turbid waters in Tarbela reservoir, during the pre-covid years. Similar findings by (Yunus et al. 2020) identified lesser suspended particulate matter concentrations in Vembanad lake, India, during the lockdown period. Aman et al. (2020) also concluded noticeable decline in the suspended particulate matter that causes turbidity, in Sabramati river of Ahmedabad, India during the lockdown period, using OLI-8 imagery.

The study also presented expanse in the spatial coverage of chlorophyll index and water index, indicating increase in residence time of the water (Calijuri et al. 2002), which causes increased rate of eutrophication, and this was witnessed in 2020 NDCI analysis, where although intensity of mean NDCI decreased from pre-covid years to Covid-19 year by 192%, yet its spatial coverage increased. The deposition of dead vegetative matter and suspended sediments can cause decreased capacity of reservoirs (Bishwakarma and Støle 2008), thus contributing towards declined power generation capacity.

CONCLUSION

Based on the aforementioned results and discussion it can be summed up that the Covid-19 related lockdown acted as an environmental healer, which led to repairing of the water quality of the reservoir. The lockdown period led to the closure of factories. and decline in electric and irrigation related water demands, leading to a probable enhanced stay period of water in the reservoir which led to increased NDCI. However, this positive impact of Covid-19 related lockdown requires a more detailed study, where sample collections from the reservoir can help in validating the results obtained from remotely sensed images.

The findings of the study are general in nature as it analyzes and compares the water quality, as gauged by the satellites, on decadal basis. For detailed analysis, future research in 2019 and 2020 is recommended where, month wise comparison of the variables under study can be investigated and variation in water quality can specifically be studies for pre covid and covid year. The findings of the study provide the policy makers with the fruit for thought that measures must be taken for formulating policies regarding sediment flushing and turbidity reduction on larger time scales, and plan for sustainable urban dynamics in Sobra city, located near Tarbela reservoir, and also in the upstream urban centers. Such policies can increase water holding capacity of the reservoir and thus the reservoir can stay functional even for our future generations.

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