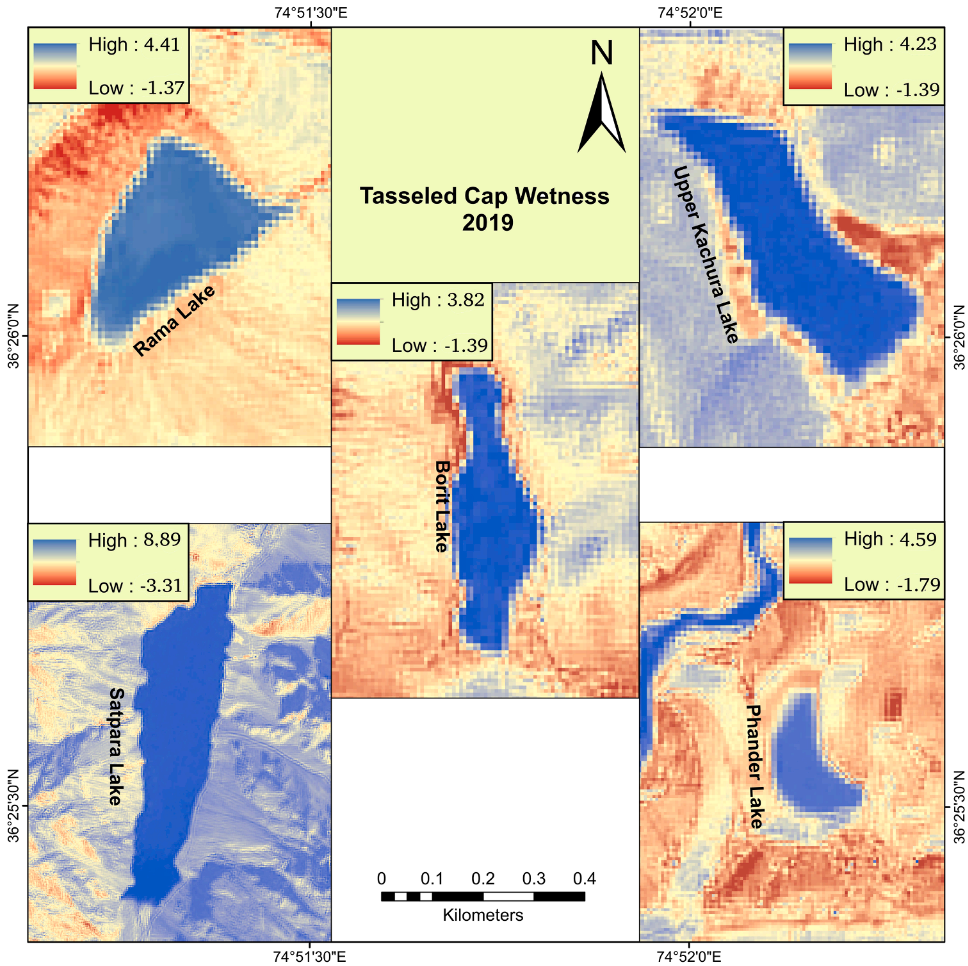

Figure 9. Tasseled Cap Wetness TCW 2019.

Table 5
TCW 2016-2019.

Lakes	TCW 2016		TCW 2019	
	High	Low	High	Low
Borith	3.79	-1.23	3.82	-1.39
Phander	4.29	-1.62	4.59	-1.79
Upper Kachura	3.31	-1.21	4.23	-1.39
Satpara	5.21	-1.65	8.89	-3.31
Rama	1.59	-8.89	4.41	-1.37

rainfall and temperature. Wetlands serve as crucial water storage areas and play a vital role in flood prevention.

3.1. Rainfall

In the northern areas of Pakistan, the ratio of rainfall is notably higher than in other regions [43–46]. Fig. 3 illustrates the rainfall pattern of the study area in 2016 and 2019. Comparing the two years, it is evident that the maximum recorded rainfall in 2019 was 11,513 mm, compared to 8,913 mm in 2016. Additionally, the minimum recorded rainfall in 2019 was 523 mm, which is higher than the rainfall of 409 mm in 2016. The study area experienced varying amounts of rainfall in the selected wetlands between 2016 and 2019, as presented in Table 2. Table 2 shows the amount of rainfall in all lakes, with a larger ratio of rainfall in 2019 compared to 2016. However, rainfall in Borith Lake was lower in 2019 (2,673 mm) than in 2016 (3,646 mm). These findings emphasize the importance of understanding the relationship between wetlands and rainfall patterns for effective wetland conservation and restoration efforts. Proper management and conservation of wetlands can help maintain their biodiversity and ecological functions, benefiting both the environment and the human communities that depend on them [47–49].

3.2. Land Surface Tempretature (LST)

The results presented in Fig. 4 display the (LST) of the study area in Gilgit Baltistan (GB) for the years 2016 and 2019, focusing on the areas where the selected wetlands are located. LST represents the surface temperature of the Earth's features and is influenced by climate change, making it one of the contributing factors to global warming. LST has a significant impact on the ecosystems of wetlands, affecting the flora and fauna species residing in these ponds, lakes, and wetland areas [50]. The LST data for the study area indicates an overall decrease in the highest temperature recorded in 2019 compared to 2016. The highest temperature in 2016 was measured at 30.65°C, showing a decrease of approximately 0.5°C in 2019, with a temperature of 30.01°C. On the other hand, the lowest temperature recorded in 2016 was -17.20°C, and this increased by about -5°C in 2019, reaching a temperature of -17.79°C. Table 3 presents the LST values of the selected wetlands for both 2016 and 2019. In general, the LST values show a decrease in all wetlands, indicating a changing weather pattern in the study area. This decrease in LST could have implications for the wetland ecosystems, affecting the behavior and distribution of flora and fauna species within these habitats [51]. The observed changes in LST highlight the importance of monitoring temperature trends in wetland areas, as they can

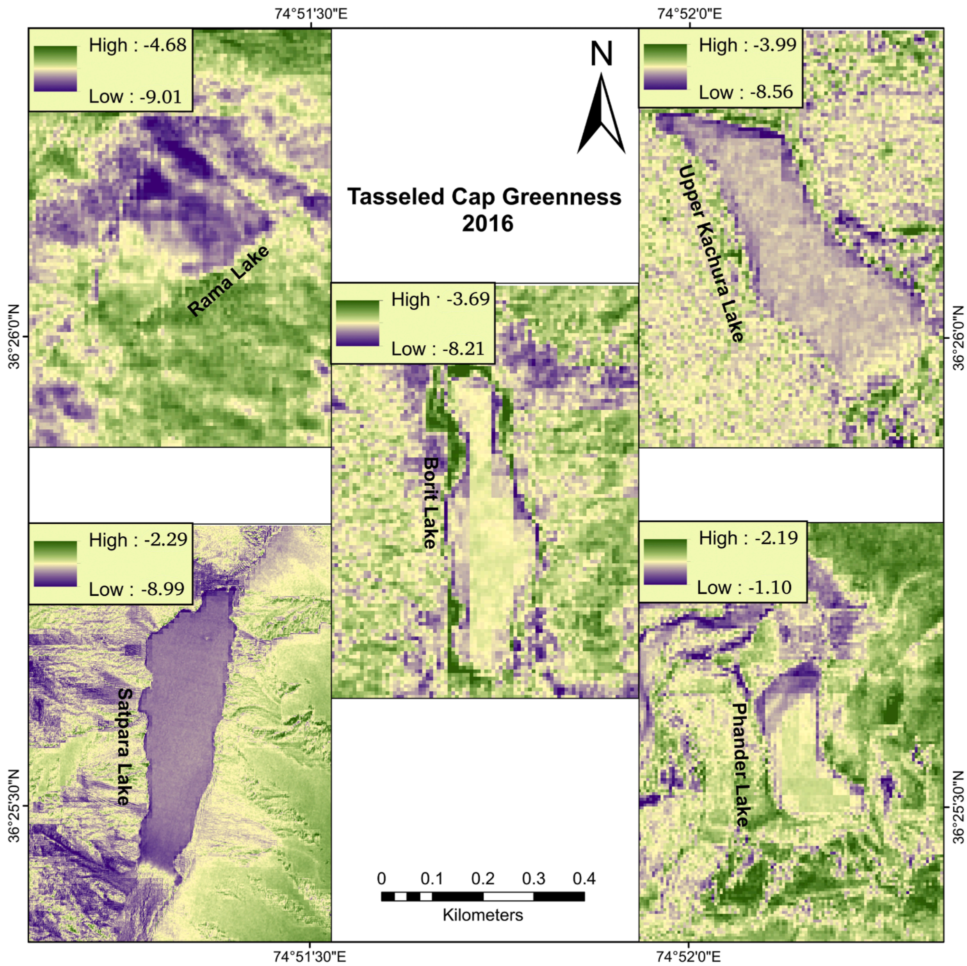

Figure 10. Tasseled Cap Greenness 2016.

have significant ecological implications. Understanding these temperature variations can help researchers and policymakers make informed decisions about wetland conservation and management to ensure the sustainability and health of these critical ecosystems in the face of climate change [52].

3.3. Digital Elevation Model (DEM)

In Fig. 5, the DEM was produced using the ASTER satellite product with a resolution of 10 meters (spatial), providing detailed elevation information for the study area. The acquired DEM data underwent a series of processing steps to enhance its accuracy and utility.

The following procedure was adopted to process the acquired DEM data:

- Filling depression spots: Depression spots in the DEM were filled to ensure smooth and continuous flow of water across the terrain.
- Flow direction: The flow direction of water across the landscape was determined based on the elevation data, establishing the paths that water would naturally follow.
- Flow accumulation: The accumulated flow at each cell of the DEM was calculated, indicating areas with higher water flow and potential stream locations.
- Stream network: Using the flow accumulation values, a detailed drainage network system was obtained, revealing the interconnected streams and rivers in the study area.
- Watershed boundaries identification: Based on the stream network and flow accumulation, the boundaries of watersheds were identified. Watersheds are tracts of land where all of the water drains to a single point, such as a river or a lake.
- The detail of the fine drainage network system was developed further by estimating the stream network based on the flow accumulation data. A stream to feature technique was also used to extract detailed stream features from the processed data.

By following this sequence of steps, the researchers were able to derive a comprehensive and accurate representation of the drainage system and watershed boundaries in the study area. This information is essential for understanding the flow of water and the hydrological characteristics of the landscape, aiding in various environmental and water resource management applications.

3.4. Landuse Landcover (LULC)

To increase classification accuracy in the large study area, the researchers separated it into five distinct sections: Borith, Phandar, Uper Kachura, Satpara, and Rama Lake, as illustrated in Figs. 6 and 7. These wetlands are very important for Waterfowl Habitat, emphasising their ecological importance. Aside from classifying the research area as wetland, the region's Land Use Land Cover (LULC) types were classified into four key groups: soil, snow, water, and vegetation. The LULC forms were classified using supervised classification approaches, which rely on the identification of training samples. These training samples were found using Google Earth imagery and field surveys, resulting in accurate classification findings [53]. The researchers were able to collect more exact information about the wetlands and their surrounding land

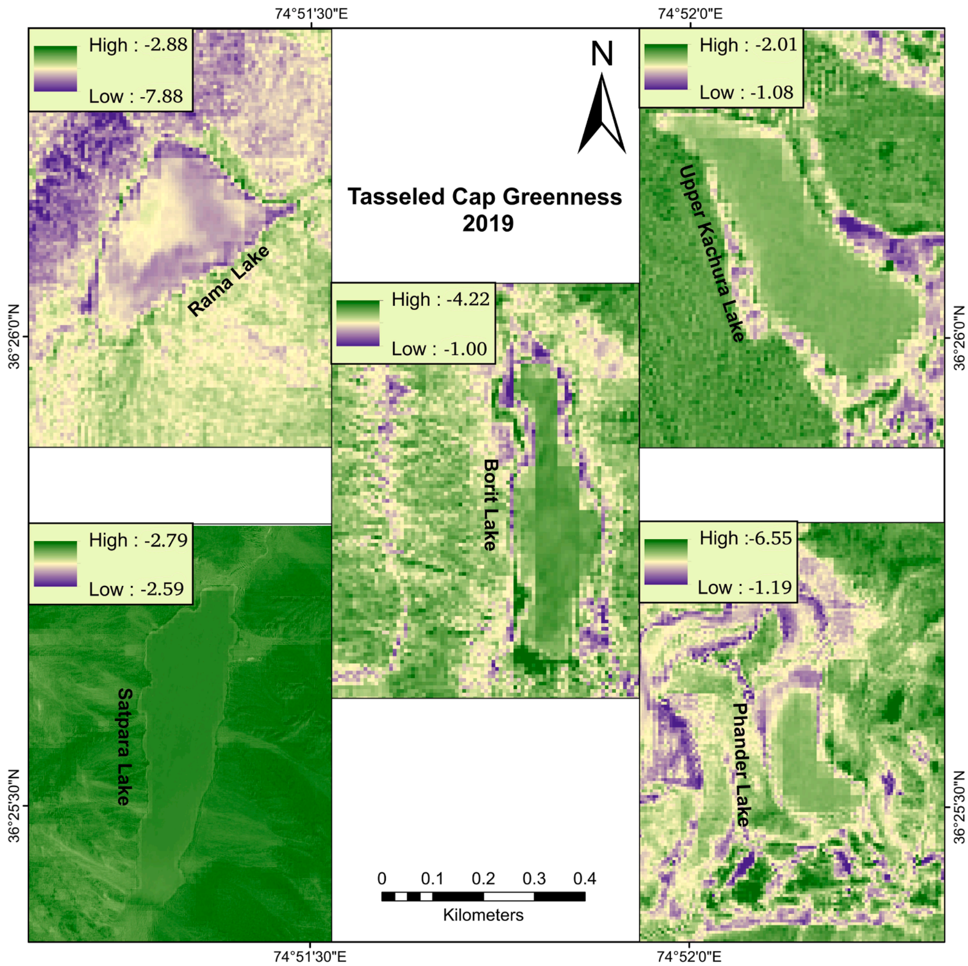

Figure 11. Tasseled Cap Greenness 2019.

Table 6
TCG 2016-2019.

Lakes	TCG 2016		TCG 2019	
	High	Low	High	Low
Borith	-3.69	-8.21	-4.22	-1.00
Phander	-2.19	-1.10	-6.55	-1.19
Upper Kachura	-3.99	-8.56	-2.01	-1.08
Satpara	-2.29	-8.99	-2.79	-2.59
Rama	-4.68	-9.01	-2.88	-7.88

cover types by separating the study area into sections and correctly identifying the LULC forms. This precise classification is required for a variety of environmental studies, conservation efforts, and land management methods in the studied region.

Table 4 presents the land use classification results for all the images in the study, comparing the years 2016 and 2019. The land use classification shows the distribution of different land cover types in the vicinity of the lakes. In 2016, the foremost areas of all lakes were covered with soil, but the percentage of soil coverage varied for each lake. For instance, in 2016, Borith Lake had 85.5% soil coverage, Phander Lake had 76%, Upper Kachura Lake had 72%, Satpara Lake had 31.2%, and Rama Lake had no soil coverage. In 2019, significant changes in soil coverage were observed. Except for Satpara Lake, all the other lakes had 0% soil coverage, indicating a soil has clearly changed distribution from 2016 to 2019. Similarly, the distribution of other land cover classes like vegetation and water also exhibited noticeable changes between 2016 and 2019. In 2016, vegetation occupied varying percentages for different lakes (3.9%, 22.9%, 21.7%, 28.6%, and 69.3%), and water covered 4.1%, 1.7%, 7.5%, 27.6%, and 4.8% for each lake, respectively. In 2019, the percentage of vegetation decreased significantly in all lakes (87.7%, 77.2%, 59.5%, 81.6%, and 62.8%), indicating a reduction in vegetation coverage. Additionally, water coverage also exhibited changes, with some lakes experiencing a decrease (5.8%, 16.7%, 30.9%, 1.9%) and Satpara Lake showing an increase (28.3%) in water coverage. These changes in land-use and landcover demonstrate significant transformations in the study area over the course of the three-year period, highlighting the importance of monitoring and understanding the dynamics of these ecosystems for effective conservation and management measures [54]. The accuracy of the LULC supervised classification was assessed using standard procedures. A stratified random sample of 500 points was generated and labeled based on visual interpretation of high-resolution satellite imagery. Error matrices were constructed to compare the classification results to these reference points [55]. The overall accuracy was 82% with a Kappa coefficient of 0.78, indicating a good level of agreement. The user's accuracies for the individual classes ranged from 78% to 91%, while the producer's accuracies varied between 81% to 89%. Water bodies had the highest accuracy, followed by vegetation and soil. The relatively high accuracies can be attributed to the representative training data used in the supervised classification. However, some confusion existed between bare soil and built-up areas. While the classification accuracy was satisfactory, future work could potentially improve results by using larger training data, incorporating topographic data, and applying post-classification refinements [13].

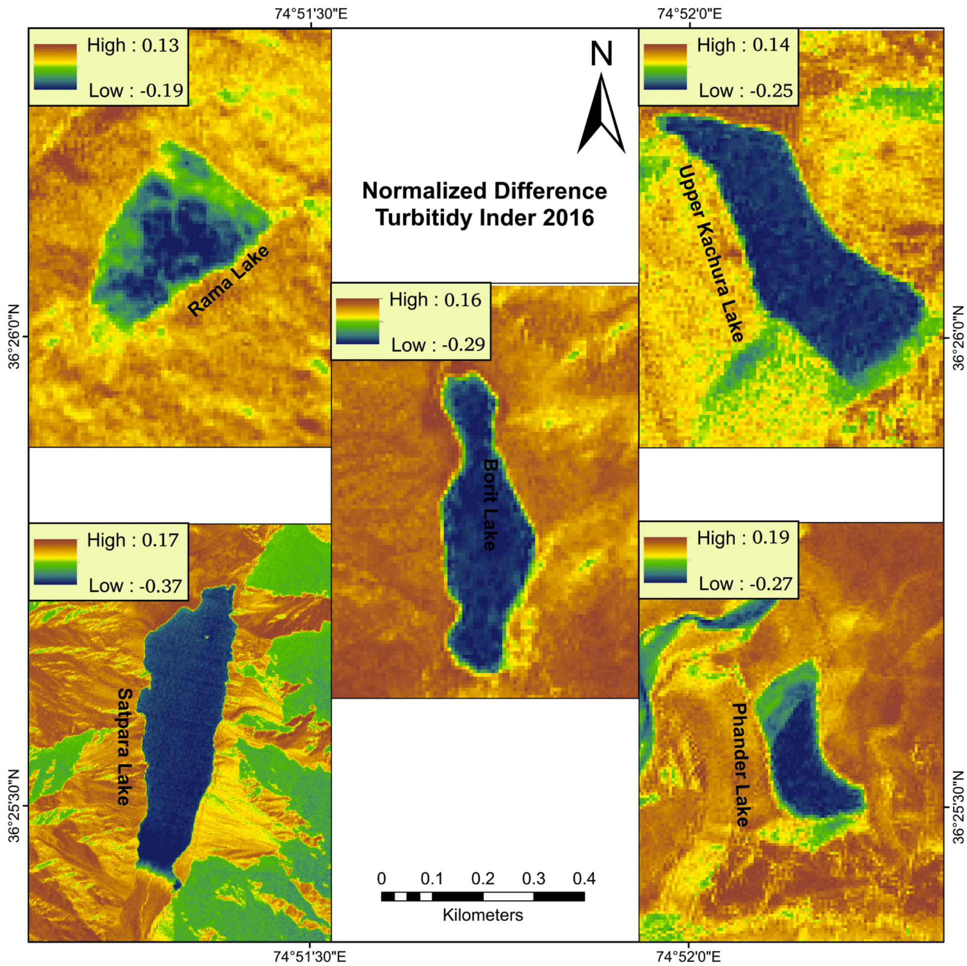

Figure 12. Normalized Difference Turbidity Index (NDTI) 2016.

3.5. Tasseled Cap Wetness (TCW)

Wetlands are home to diverse ecosystems, showcasing unique flora and fauna. They provide multidimensional services that have significance in both natural and commercial perspectives, contributing to natural cycles and the economy [56] (Figs. 8, 9, and Table 5). The analysis of all lakes, reveals the wetness levels in the study area. In both 2016 and 2019, Satpara Lake exhibited the highest wetness values, represented by blue shades in the images. The wetness values for Satpara Lake were 5.21 in 2016 and increased to 8.89 in 2019. For the other lakes, the highest wetness values in 2016 were 3.79 for Borith Lake, 4.29 for Phander Lake, 3.31 for Upper Kachura Lake, and 1.59 for Rama Lake. In 2019, these values changed to 3.82, 4.59, 4.23, and 4.41, respectively. Conversely, the lowest areas for wetness, represented by red shades in both 2016 and 2019, were observed in all lakes. These wetness patterns provide valuable information about the hydrological characteristics of the lakes and the overall wetland ecosystem dynamics. Understanding the wetness variations in wetlands can help researchers and policymakers assess the health of these critical ecosystems and implement appropriate conservation and management strategies to safeguard their ecological value and contributions to the environment and economy [57].

3.6. Tasseled Cap Greenness (TCG)

The (TCG) assessment was performed on all of the lakes chosen, and the results revealed varying levels of greenness. These variations in greenness values are directly linked to the growth of microorganisms in the wetland ecosystem (Figs. 10 and 11). In 2016, Borith Lake had the highest TCG value of -3.69 and the lowest value of -8.21. However, in 2019, the highest TCG value for Borith Lake was -4.22, and the lowest value was -1.00, indicating a change in greenness between 2016 and 2019. Similarly, Lakes had TCG values of -2.19, -3.99, -2.29, and -4.68, respectively, as the highest greenness values in 2016. In 2019, these values changed to -6.55, -2.01, -2.79, and -2.88, respectively. Furthermore, the lowest greenness values also showed variations between 2016 and 2019. For example, Phander Lake had a lowest TCG value of -1.10 in 2016, which changed to -1.19 in 2019. Upper Kachura, Satpara, and Rama had lowest values of -8.56, -8.99, and -9.01 in 2016, respectively. In 2019, these values changed to -1.08, -2.59, and -7.88, respectively. These changes in greenness values are visually represented in the images, where green areas indicate the highest levels of greenness, while purple shades highlight the lowest zones of greenness. Understanding the variations in greenness is essential for assessing the health and productivity of wetland ecosystems. Changes in greenness can indicate shifts in the growth of vegetation and microorganisms, which have ecological implications for the wetlands and the organisms that depend on them. The study's focus was on wetland dynamics, but similar machine learning techniques could be applied to crop type mapping [58]. Monitoring these changes can aid in better management and conservation strategies to preserve the biodiversity and functionality of these valuable ecosystems [59,60] (Table 6).

3.7. Normalized Difference Turbidity Index (NDTI)

The Turbidity Index analysis provided information about the water

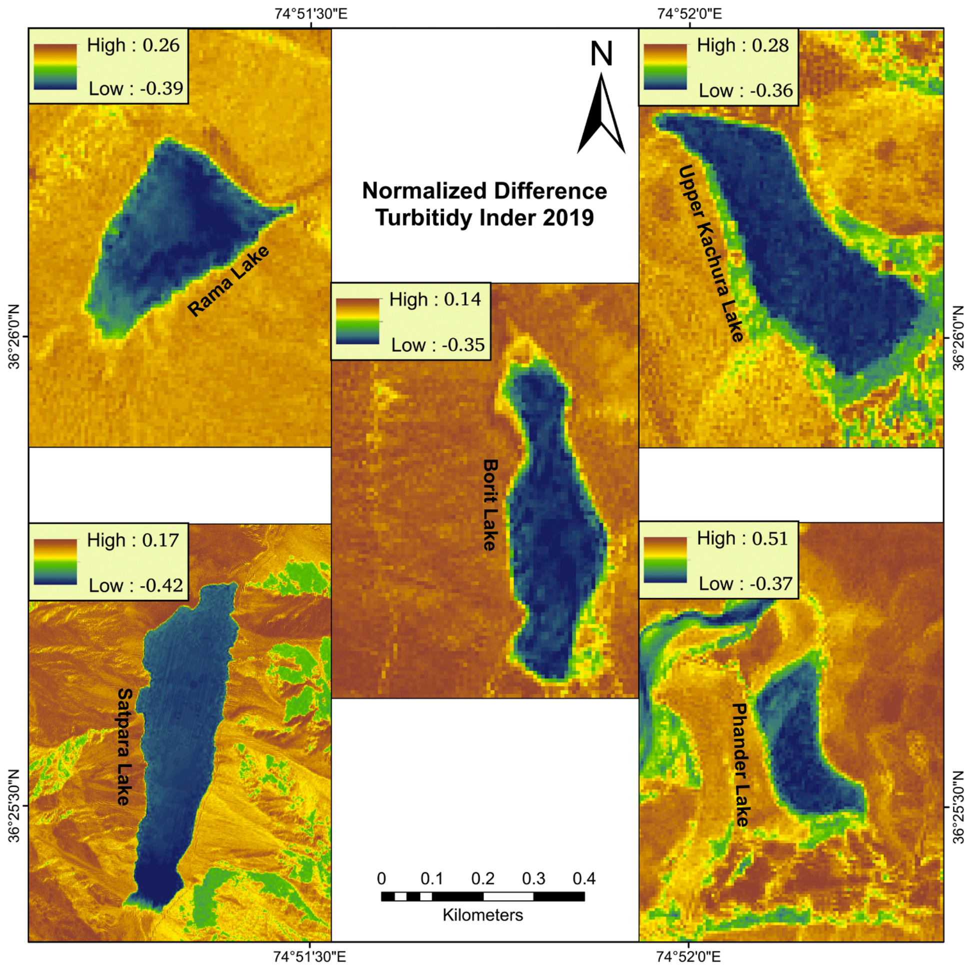

Figure 13. Normalized Difference Turbidity Index (NDTI) 2019.

Table 7
NDTI of 2016-2019.

Lakes	2016		2019	
	High	Low	High	Low
Borith	0.16	-0.29	0.14	-0.35
Phander	0.19	-0.27	0.51	-0.37
Upper Kachura	0.14	-0.25	0.28	-0.36
Satpara	0.17	-0.37	0.17	-0.42
Rama	0.13	-0.19	0.26	-0.39

quality in the selected lakes (Figs. 12 and 13). In the images for 2016 and 2019, the orange shade represented the highest turbidity levels, while the blue color indicated low turbidity levels. Overall, the lakes showed generally low turbidity. In 2016, the highest turbidity values for Borith, Phander, Upper Kachura, Satpara, and Rama Lake were 0.16, 0.19, 0.14, 0.17, and 0.13, respectively. However, in 2019, these values changed to 0.14, 0.51, 0.28, 0.17, and 0.26, respectively, indicating a change in turbidity levels between the two years. Similarly, the lowest turbidity values also exhibited changes from 2016 to 2019. In 2016, the lowest turbidity values were -0.29, -0.27, -0.25, -0.37, and -0.19 for all Lake, respectively. In 2019, these values changed to -0.35, -0.37, -0.36, -0.42, and -0.39, respectively. Turbidity is a critical parameter for assessing water quality, as it reflects the amount of suspended particles in the water. Changes in turbidity levels can have implications for water clarity, aquatic habitat, and the overall health of the wetland ecosystem. Researchers and politicians can get insights into the environmental state of the lakes by monitoring turbidity levels and making informed judgements about water quality management and conservation activities (Table 7).

3.8. Change Detection (CD)

The purpose of identifying changes in land use is to understand the transformations that have occurred in the past and to determine how land use has evolved over time. This analysis provides valuable insights into the rate and nature of land use changes. For the change detection analysis in this study, spatially strong data from GE images of the lakes were utilized to compare the conditions in 2016 and 2019 (Fig. 14 a-e). The boundary in green represented the lake area in 2016, while the red boundary represented the lake boundaries in 2019. Furthermore, the water area was highlighted with a blue shade in 2016 and a yellow colour in 2019, highlighting the changes visually. In 2016, the percentage of water area in each lake was as follows: Phander 20.79%, Borith 22.73%, Upper Kachura 23.03%, Satpara 23.01%, and Rama 24.63%. The total area of each lake was recorded as 29.89%, 28.09%, 27.88%, 29.12%, and 26.10%, respectively. In 2019, slight changes were observed in both the boundary of the lake and the percentage of water area. For instance, in 2019 [65,66], Phander Lake had 30.10% of the total area, Borith Lake had 29.40%, Upper Kachura Lake had 29.13%, Satpara Lake had 28.82%, and Rama Lake had 27.20% of the area. The percentage of water area also changed in 2019, becoming 22.10%, 23.40%, 24.56%, 22.43%, and 25.01%, respectively. These results demonstrate the alterations that have occurred in the lake boundaries and water percentages over the three-year period. Understanding these changes is crucial for monitoring the health of the

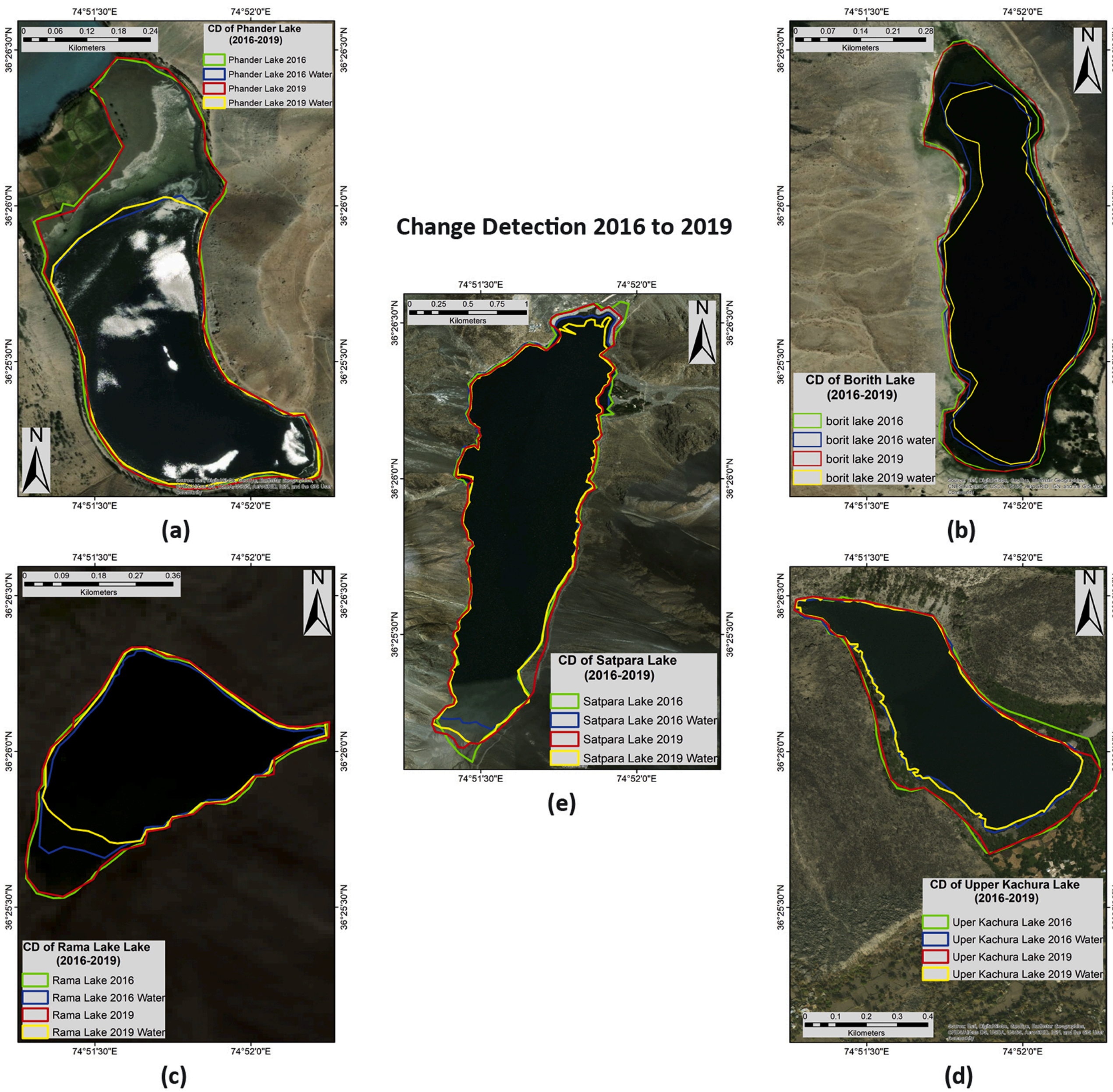

Figure 14. (a) Change Detection of Phander Lake 2016 and 2019, **(b).** Change Detection of Borith Lake 2016 and 2019, **(c).** Change Detection of Rama Lake 2016 and 2019, **(d).** Change Detection of Upper Kachura Lake 2016 and 2019 and **(e).** Change Detection of Satpara Lake 2016 and 2019.

Table 8
Change Detection of Lakes 2016-2019.

Lakes	2016		2019	
	Water	Area Sq.km	Water	Area Sq. Km
Borith	22.73	28.09	23.40	29.40
Phander	20.79	29.89	22.10	30.10
Upper Kachura	23.01	29.12	22.43	28.82
Satpara	24.63	26.10	25.01	27.20
Rama	23.03	27.88	24.56	29.13

wetland ecosystems and for making informed decisions regarding their conservation and management [61–64] (Table 8).

4. Conclusions

The study aimed to identify neglected wetlands in Pakistan using remote sensing techniques and to analyze their dynamics over a period of 2016-2019. The study identified several neglected wetlands in Pakistan that have been subject to various human-induced changes. The analysis showed that wetlands in Pakistan are highly vulnerable to human activities, such as land-use changes and urbanization, which have a significant impact on their distribution and change. The study highlights the potential of remote sensing techniques for identifying and monitoring neglected wetlands in Pakistan. Remote sensing data proved to be a valuable tool for mapping wetland change and analyzing the factors influencing wetland dynamics. The findings of this study can guide policymakers and stakeholders in making informed decisions related to wetland conservation and management in Pakistan. The study's wetland conservation and management strategies are tailored to the specific needs and challenges of neglected wetlands in Pakistan and could contribute to improving wetland management and conservation in the country. In conclusion, this study provides a comprehensive understanding of wetland dynamics in Pakistan, particularly neglected wetlands. The study contributes towards achieving the sustainable development goals by providing valuable information for preserving these ecosystems, which are essential for maintaining biodiversity, regulating climate, and supporting the livelihoods of local communities. The study also highlights the need for continued monitoring and conservation efforts to protect Pakistan's wetlands from further degradation and loss. Our investigation found that the wetlands' dynamics have changed between 2016 and 2019. Some wetlands changed negatively, while others changed positively, most likely as a result of climate change and increased human-induced activities that directly or indirectly impact the wetland ecology.

Author Contributions

RWA and HS: Conceptualization; methodology; software; RWA, SP, HS, AQ, DR, FM and KJ: validation, formal analysis; investigation; HS: resources; data curation; RWA, KJ, BA, SA, WAH and SP; writing—original draft preparation.; writing—review and editing; visualization, RWA.; supervision, HS; project administration, HS.; funding acquisition, HS. All authors contributed equally.

Funding

This work is supported by the Special Research Funding of LIESMARS at Wuhan University, China. The authors extend their appreciation to the Researchers supporting project number (RSP2023R384) King Saud University, Riyadh, Saudi Arabia

Ethical Approval

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Availability of data and materials

data available upon request to correspondaning author.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

Author would like to aknkowledge anonymous reviewer for their contribution to this manuscript. The authors extend their appreciation to the Researchers supporting project number (RSP2023R384) King Saud University, Riyadh, Saudi Arabia

References

[1] M. Esmaeili, D. Abbasi-Moghadam, A. Sharifi, A. Tariq, Q. Li, Hyperspectral Image Band Selection Based on CNN Embedded GA (CNNeGA), IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 16 (2023) 1927–1950, https://doi.org/10.1109/JSTARS.2023.3242310.

[2] L. Jansen, A. Di Gregorio, Land Cover Classification System (LCCS): Classification Concepts and User Manual, 2000.

[3] M. Elhag, I. Gitas, A. Othman, J. Bahrawi, P. Gikas, Assessment of Water Quality Parameters Using Temporal Remote Sensing Spectral Reflectance in Arid Environments, Saudi Arabia, Water 11 (2019) 556, https://doi.org/10.3390/w11030556.

[4] K. Lim, D. Jin, C.-S. Kim, Change Detection in High Resolution Satellite Images Using an Ensemble of Convolutional Neural Networks, in: 2018 Asia-Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA ASC), IEEE, 2018, pp. 509–515, https://doi.org/10.23919/APSIPA.2018.8659603.

[5] S. Ghaderizadeh, D. Abbasi-Moghadam, A. Sharifi, A. Tariq, S. Qin, Multiscale Dual-Branch Residual Spectral–Spatial Network With Attention for Hyperspectral Image Classification, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 15 (2022) 5455–5467, https://doi.org/10.1109/JSTARS.2022.3188732.

[6] M. Mohammadi, A. Sharifi, M. Hosseingholizadeh, A. Tariq, Detection of Oil Pollution Using SAR and Optical Remote Sensing Imagery: A Case Study of the Persian Gulf, J. Indian Soc. Remote Sens. 49 (2021) 2377–2385, https://doi.org/10.1007/s12524-021-01399-2.

[7] A. Sharifi, J. Amini, J.T. Sri Sumantyo, R. Tateishi, Speckle Reduction of PolSAR Images in Forest Regions Using Fast ICA Algorithm, J. Indian Soc. Remote Sens. 43 (2015) 339–346, https://doi.org/10.1007/s12524-014-0423-3.

[8] A. Tariq, S. Qin, Spatio-temporal variation in surface water in Punjab, Pakistan from 1985 to 2020 using machine-learning methods with time-series remote sensing data and driving factors, Agric. Water Manag. 280 (2023), 108228, https://doi.org/10.1016/j.agwat.2023.108228.

[9] A. Sharifi, J. Amini, R. Tateishi, Estimation of forest biomass using multivariate relevance vector regression, Photogramm. Eng. Remote Sensing. 82 (2016) 41–49, https://doi.org/10.14358/PERS.83.1.41.

[10] B. Jiang, Z. Ouyang, H. Miao, H. Zheng, Y. Bai, C. Zhuang, Y. Fang, Ecosystem services valuation of the Haihe river basin wetlands, Shengtai Xuebao/Acta Ecol. Sin. 31 (2011) 2236–2244.

[11] Y. Du, L. Pei, J. Liu, Q. Kong, F. Xu, Q. Wang, C. Zhao, R. Wang, Chemical Strategy of the Invasive Plant Alternanthera philoxeroides Leading Ecological Adaptation in Constructed Wetlands, Chiang Mai J. Sci. 47 (2020) 899–911.

[12] A. Zamani, A. Sharifi, S. Felegari, A. Tariq, N. Zhao, Agro Climatic Zoning of Saffron Culture in Miyaneh City by Using WLC Method and Remote Sensing Data, Agriculture 12 (2022) 118, https://doi.org/10.3390/agriculture12010118.

[13] A. Sharifi, Flood Mapping Using Relevance Vector Machine and SAR Data: A Case Study from Aqqala, Iran, J. Indian Soc. Remote Sens (2020), https://doi.org/10.1007/s12524-020-01155-y.

[14] K.L. Erwin, Wetlands and global climate change: the role of wetland restoration in a changing world, Wetl. Ecol. Manag. 17 (2009) 71–84, https://doi.org/10.1007/s11273-008-9119-1.

[15] K. Banach, A.M. Banach, L.P.M. Lamers, H. De Kroon, R.P. Bennicelli, A.J.M. Smits, E.J.W. Visser, Differences in flooding tolerance between species from two wetland habitats with contrasting hydrology: implications for vegetation development in future floodwater retention areas, Ann. Bot. 103 (2009) 341–351, https://doi.org/10.1093/aob/mcn183.

[16] G.E. Adjovu, H. Stephen, S. Ahmad, Spatial and Temporal Dynamics of Key Water Quality Parameters in a Thermal Stratified Lake Ecosystem: The Case Study of Lake Mead, Earth 4 (2023) 461–502, https://doi.org/10.3390/earth4030025.

[17] A. Sharifi, M. Hosseingholizadeh, The Effect of Rapid Population Growth on Urban Expansion and Destruction of Green Space in Tehran from 1972 to 2017, J. Indian Soc. Remote Sens. 47 (2019) 1063–1071, https://doi.org/10.1007/s12524-019-00966-y.

[18] Y. Liu, L. Liu, L. Li, H. Li, H. Xu, J. Yang, S. Tao, B. Zhu, Changes in Runoff in the Source Region of the Yellow River Basin Based on CMIP6 Data under the Goal of Carbon Neutrality, Water 15 (2023) 2457, https://doi.org/10.3390/w15132457.

[19] M. Gao, Z. Qin, H. Zhang, L. Lu, X. Zhou, X. Yang, Remote Sensing of Agro-droughts in Guangdong Province of China Using MODIS Satellite Data, Sensors 8 (2008) 4687–4708, https://doi.org/10.3390/s8084687.

[20] T.S. Le, R. Harper, B. Dell, Application of Remote Sensing in Detecting and Monitoring Water Stress in Forests, Remote Sens 15 (2023) 3360, https://doi.org/10.3390/rs15133360.

[21] Q. Gu, J. Kang, S. Gao, Y. Zhao, H. Yi, X. Zha, Eukaryotic Translation Elongation Factor OsEF1A Positively Regulates Drought Tolerance and Yield in Rice, Plants 12 (2023) 2593, https://doi.org/10.3390/plants12142593.

[22] P.-R. Guo, L.-L. Wu, Y. Wang, D. Liu, J.-A. Li, Effects of Drought Stress on the Morphological Structure and Flower Organ Physiological Characteristics of Camellia oleifera Flower Buds, Plants 12 (2023) 2585, https://doi.org/10.3390/plants12132585.

[23] A.R.P. Zefrehei, M. Kolahi, J. Fisher, Modeling Wetland Restoration Scenarios in Gavkhooni International Wetland, Restor. Ecol. (2022), https://doi.org/10.1111/rec.13721.

[24] T. Xu, B. Weng, D. Yan, K. Wang, X. Li, W. Bi, M. Li, X. Cheng, Y. Liu, Wetlands of International Importance: Status, Threats, and Future Protection, Int. J. Environ. Res. Public Health. 16 (2019) 1818, https://doi.org/10.3390/ijerph16101818.

[25] A. Kosari, A. Sharifi, A. Ahmadi, M. Khoshsima, Remote sensing satellite's attitude control system: rapid performance sizing for passive scan imaging mode, Aircr. Eng. Aerosp. Technol. 92 (2020) 1073–1083, https://doi.org/10.1108/AEAT-02-2020-0030.

[26] A. Sharifi, J. Amini, Forest biomass estimation using synthetic aperture radar polarimetric features, J. Appl. Remote Sens. 9 (2015), 097695, https://doi.org/10.1117/1.JRS.9.097695.

[27] S.M.M. Nejad, D. Abbasi-Moghadam, A. Sharifi, N. Farmonov, K. Amankulova, M. Laszlz, Multispectral Crop Yield Prediction Using 3D-Convolutional Neural Networks and Attention Convolutional LSTM Approaches, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 16 (2023) 254–266, https://doi.org/10.1109/JSTARS.2022.3223423.

[28] R.W. Aslam, H. Shu, A. Yaseen, A. Sajjad, S.Z.U. Abidin, Identification of time-varying wetlands neglected in Pakistan through remote sensing techniques, Environ. Sci. Pollut. Res. 30 (2023) 74031–74044, https://doi.org/10.1007/s11356-023-27554-5.

[29] R.W. Aslam, H. Shu, A. Yaseen, Monitoring the population change and urban growth of four major Pakistan cities through spatial analysis of open source data, Ann. GIS. (2023) 1–13, https://doi.org/10.1080/19475683.2023.2166989.

[30] K. Nielsen, O.B. Andersen, H. Ranndal, Validation of Sentinel-3A Based Lake Level over US and Canada, Remote Sens 12 (2020) 2835, https://doi.org/10.3390/rs12172835.

[31] R. Costanza, R. de Groot, P. Sutton, S. van der Ploeg, S.J. Anderson, I. Kubiszewski, S. Farber, R.K. Turner, Changes in the global value of ecosystem services, Glob. Environ. Chang. 26 (2014) 152–158, https://doi.org/10.1016/j.gloenvcha.2014.04.002.

[32] R.C. Gardner, S. Barchiesi, C. Beltrame, C.M. Finlayson, T. Galewski, I. Harrison, M. Paganini, C. Perennou, D. Pritchard, A. Rosenqvist, M. Walpole, State of the World's Wetlands and Their Services to People: A Compilation of Recent Analyses, SSRN Electron. J. (2015), https://doi.org/10.2139/ssrn.2589447.

[33] V.R. Barros, C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, Climate Change 2014: Impacts, Adaptation and Vulnerability, Cambridge University Press, Cambridge, 2014, https://doi.org/10.1017/CBO9781107415386.

[34] M. Shahzaman, W. Zhu, I. Ullah, F. Mustafa, M. Bilal, S. Ishfaq, S. Nisar, M. Arshad, R. Iqbal, R.W. Aslam, Comparison of Multi-Year Reanalysis, Models, and Satellite Remote Sensing Products for Agricultural Drought Monitoring over South Asian Countries, Remote Sens 13 (2021) 3294, https://doi.org/10.3390/rs13163294.

[35] J. Tan, D. Yu, Q. Li, X. Tan, W. Zhou, Spatial relationship between land-use/land-cover change and land surface temperature in the Dongting Lake area, China, Sci. Rep. 10 (2020) 9245, https://doi.org/10.1038/s41598-020-66168-6.

[36] P. Dambach, V. Machault, J.-P. Lacaux, C. Vignolles, A. Sié, R. Sauerborn, Utilization of combined remote sensing techniques to detect environmental variables influencing malaria vector densities in rural West Africa, Int. J. Health Geogr. 11 (2012) 8, https://doi.org/10.1186/1476-072X-11-8.

[37] R. Gardner, M. Finlayson, Global Wetland Outlook: State of the World's Wetlands and Their Services to People, 2018.

[38] A. Sharifi, Estimation of biophysical parameters in wheat crops in Golestan province using ultra-high resolution images, Remote Sens. Lett. 9 (2018) 559–568, https://doi.org/10.1080/2150704X.2018.1452058.

[39] W. Ciężkowski, S. Szporak-Wasilewska, M. Kleniewska, J. Jóźwiak, T. Gnatowski, P. Dąbrowski, M. Góraj, J. Szatyłowicz, S. Ignar, J. Chormański, Remotely Sensed Land Surface Temperature-Based Water Stress Index for Wetland Habitats, Remote Sens 12 (2020) 631, https://doi.org/10.3390/rs12040631.

[40] S. Bid, G. Siddique, Identification of seasonal variation of water turbidity using NDTI method in Panchet Hill Dam, India, Model. Earth Syst. Environ. 5 (2019) 1179–1200, https://doi.org/10.1007/s40808-019-00609-8.

[41] A. Tariq, F. Mumtaz, A series of spatio-temporal analyses and predicting modeling of land use and land cover changes using an integrated Markov chain and cellular automata models, Environ. Sci. Pollut. Res. (2023) 15, https://doi.org/10.1007/s11356-023-25722-1.

[42] X. Zhang, S. Fu, Z. Hu, J. Zhou, X. Zhang, Changes Detection and Object-Oriented Classification of Major Wetland Cover Types in Response to Driving Forces in Zoige County, Eastern Qinghai–Tibetan Plateau, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 14 (2021) 9297–9305, https://doi.org/10.1109/JSTARS.2021.3104223.

[43] I. Fayad, N. Baghdadi, J.S. Bailly, F. Frappart, M. Zribi, Analysis of GEDI Elevation Data Accuracy for Inland Waterbodies Altimetry, Remote Sens 12 (2020) 2714, https://doi.org/10.3390/rs12172714.

[44] Z. Yao, B. Wang, J. Huang, Y. Zhang, J. Yang, R. Deng, Q. Yang, Analysis of Land Use Changes and Driving Forces in the Yanhe River Basin from 1980 to 2015, J. Sensors. 2021 (2021) 1–11, https://doi.org/10.1155/2021/6692333.

[45] S.A. Hussain, F.-Q. Han, W. Han, A. Rodríguez, J.-L. Han, J. Han, X.-Q. Nian, L. Yi, Z. Ma, D. Widory, Climate Change Impact on the Evolution of the Saline Lakes of the Soan-Sakaser Valley (Central Salt Range; Pakistan): Evidences from Hydrochemistry and Water (δD, δ18O) and Chlorine (δ37Cl) Stable Isotopes, Water 11 (2019) 912, https://doi.org/10.3390/w11050912.

[46] L. Comte, J.D. Olden, P.A. Tedesco, A. Ruhi, X. Giam, Climate and land-use changes interact to drive long-term reorganization of riverine fish communities globally, in: Proc. Natl. Acad. Sci 118, 2021, https://doi.org/10.1073/pnas.2011639118.

[47] G.-S. Bahn, B.-C. An, Analysis of Environmental Purification Effect of Riparian Forest with Poplar Trees for Ecological Watershed Management: A Case Study in the Floodplain of the Dam Reservoir in Korea, Sustainability 12 (2020) 6871, https://doi.org/10.3390/su12176871.

[48] R. Mugo, R. Waswa, J.W. Nyaga, A. Ndubi, E.C. Adams, A.I. Flores-Anderson, Quantifying Land Use Land Cover Changes in the Lake Victoria Basin Using Satellite Remote Sensing: The Trends and Drivers between 1985 and 2014, Remote Sens 12 (2020) 2829, https://doi.org/10.3390/rs12172829.

[49] X. Lu, S. Zhang, Y. Tian, Y. Li, R. Wen, J. Tsou, Y. Zhang, Monitoring Suaeda salsa Spectral Response to Salt Conditions in Coastal Wetlands: A Case Study in Dafeng Elk National Nature Reserve, 12, Remote Sens, China, 2020, p. 2700, https://doi.org/10.3390/rs12172700.

[50] A. Sajjad, J. Lu, R.W. Aslam, M. Ahmad, Flood Disaster Mapping Using Geospatial Techniques: A Case Study of the 2022 Pakistan Floods, in: ECWS-7 2023, MDPI, Basel Switzerland, 2023, p. 78, https://doi.org/10.3390/ECWS-7-14312.

[51] A. Yaseen, J. Lu, X. Chen, Flood susceptibility mapping in an arid region of Pakistan through ensemble machine learning model, Stoch. Environ. Res. Risk Assess. 36 (2022) 3041–3061, https://doi.org/10.1007/s00477-022-02179-1.

[52] J. Li, Q. Pan, Y. Peng, T. Feng, S. Liu, X. Cai, C. Zhong, Y. Yin, W. Lai, Perceived Quality of Urban Wetland Parks: A Second-Order Factor Structure Equation Modeling, Sustainability 12 (2020) 7204, https://doi.org/10.3390/su12177204.

[53] Y. Cao, Y. Ma, T. Liu, J. Li, R. Zhong, Z. Wang, C. Zan, Analysis of Spatial–Temporal Variations and Driving Factors of Typical Tail-Reach Wetlands in the Ili-Balkhash Basin, 14, Remote Sens, Central Asia, 2022, p. 3986, https://doi.org/10.3390/rs14163986.

[54] L. Eufemia, M. Bonatti, S. Sieber, B. Schröter, M.A. Lana, Mechanisms of Weak Governance in Grasslands and Wetlands of South America, Sustainability 12 (2020) 7214, https://doi.org/10.3390/su12177214.

[55] A. Sharifi, Development of a method for flood detection based on Sentinel-1 images and classifier algorithms, Water Environ. J. 35 (2021) 924–929, https://doi.org/10.1111/wej.12681.

[56] C. Ren, B. Dong, P. Wang, L. Fang, X. Gao, H. Xu, T. Wang, Z. Xu, Y. Liu, S. Li, W. Xu, Land Use Change and Driving Force Analysis of Wetland in Poyang Lake Based on Remote Sensing, 2021. https://doi.org/10.21203/rs.3.rs-818410/v1.

[57] W.A. Wurtsbaugh, C. Miller, S.E. Null, R.J. DeRose, P. Wilcock, M. Hahnenberger, F. Howe, J. Moore, Decline of the world's saline lakes, Nat. Geosci. 10 (2017) 816–821, https://doi.org/10.1038/ngeo3052.

[58] N. Farmonov, K. Amankulova, J. Szatmari, A. Sharifi, D. Abbasi-Moghadam, S. M. Mirhoseini Nejad, L. Mucsi, Crop Type Classification by DESIS Hyperspectral Imagery and Machine Learning Algorithms, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 16 (2023) 1576–1588, https://doi.org/10.1109/JSTARS.2023.3239756.

[59] A.W. Worqlul, E.K. Ayana, Y.T. Dile, M.A. Moges, M.G. Dersseh, G. Tegegne, S. Kibret, Spatiotemporal Dynamics and Environmental Controlling Factors of the Lake Tana Water Hyacinth in Ethiopia, Remote Sens 12 (2020) 2706, https://doi.org/10.3390/rs12172706.

[60] M. Asif, J.H. Kazmi, A. Tariq, Traditional ecological knowledge based indicators for monitoring rangeland conditions in Thal and Cholistan Desert, Pakistan, Environ. Challenges. 13 (2023), 100754, https://doi.org/10.1016/j.envc.2023.100754.

[61] M.F. Baqa, F. Chen, L. Lu, S. Qureshi, A. Tariq, S. Wang, L. Jing, S. Hamza, Q. Li, Monitoring and modeling the patterns and trends of urban growth using urban sprawl matrix and CA-Markov model: A case study of Karachi, Land, Pakistan, 2021, p. 10, https://doi.org/10.3390/land10070700.

[62] A. Ahmad, S.R. Ahmad, H. Gilani, A. Tariq, N. Zhao, R.W. Aslam, F. Mumtaz, A Synthesis of Spatial Forest Assessment Studies Using Remote Sensing Data and Techniques in Pakistan, Forests 12 (2021) 1211, https://doi.org/10.3390/f12091211.

[63] A. Tariq, J. Yan, B. Ghaffar, S. Qin, B.G. Mousa, A. Sharifi, M.E. Huq, M. Aslam, Flash Flood Susceptibility Assessment and Zonation by Integrating Analytic Hierarchy Process and Frequency Ratio Model with Diverse Spatial Data, Water 14 (2022) 3069, https://doi.org/10.3390/w14193069.

[64] R. Bokhari, H. Shu, A. Tariq, N. Al-Ansari, R. Guluzade, T. Chen, A. Jamil, M. Aslam, Land subsidence analysis using synthetic aperture radar data, Heliyon 9 (2023) e14690, https://doi.org/10.1016/j.heliyon.2023.e14690.

[65] D. Raza, H. Shu, S.U. Khan, M. Ehsan, U. Saeed, H. Aslam, R.W. Aslam, M. Arshad, Comparative geospatial approach for agricultural crops identification in interfluvial plain - A case study of Sahiwal district, Pakistan, Pakistan J. Agric. Res. 59 (2022) 567–578. https://doi.org/10.21162/PAKJAS/22.127.

[66] D. Raza, S. Mirza, H. Shu, A. Khan, A. Tariq, S.U. Khan, H. Aeman, F. Akmal, Geospatial approach for petrol pumps valuation with urban prediction modelling by cellular automata in creeds of metropolitan expanse, ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. X-5/W1-202 (2023) 59–67. https://doi.org/10.5194/isprs-annals-X-5-W1-2023-59-2023.