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Leveraging machine learning and remote sensing to monitor long-term spatial-temporal wetland changes: Towards a national RAMSAR inventory in Pakistan

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ABSTRACT

In Pakistan, wetlands are of primary focus as they withstand the effects of floods, recharge groundwater, and provide several services in the context of economic, cultural, and climate mitigation aspects. However, the lack of field data and huge monitoring costs hinder their sustainable management in Pakistan. In connection with this, the current study leverages Google Earth Engine (GEE), earth observation data, and machine learning-based Random Forest (RF) algorithm to evaluate spatial-temporal heterogeneities in wetlands in Pakistan between 1990 and 2020. Additionally, the first high-resolution long-term inventory of wetlands in Pakistan is presented to provide a baseline. Our results ascertain an increase in wetlands areas over the last 30 years. The swamps' area increased from 1391.19 km^2 in 1990 to 8510.43 km^2 in 2020 (2.62% annual change rate). Similarly, the marshes area increased between 1990 and 2020 with a ~1.04% annual change rate. Conversely, the water area decreased from 8371.97 km^2 in 1990 to 7818.34 km^2 in 2020. The increase in wetlands could be associated with good conservation and planting practices in Pakistan. While these results provide important insights to implement conservation practices in the context of wetland sustainability, the resultant data is essential to the national wetlands inventory database for future evaluations.

1. Introduction

Approximately 6–7 percent of global terrestrial areas are covered with wetlands, which provide diverse services including defense against floods, climate regulations, provisioning of habitats, and economic services through tourism (Liu et al., 2013; Mao et al., 2018). Wetlands are one of the world's most productive ecosystems as they absorb pollutants, purify water, recharge groundwater, act as nutrient and sediment sinks, and provide fresh water and building material (T. Xu et al., 2019). However, anthropogenic activities threaten the sustainability of wetlands at local, regional, and global scales (T. Xu et al., 2019). Worldwide, since 1970, more than 35% of the world's wetlands have vanished (X. Xu, Chen, Yang, Jiang, & Zhang, 2020). The rate of loss varies significantly from country to country, with developing countries at relatively higher risk due to the unavailability of resources, lesser capabilities for management, and lack of awareness (A. A. Khan & Arshad, 2014).

In Pakistan, the term "wetlands" was first discussed in 1967, and on 21st December 1975, the RAMSAR convention came into action (https://www.ramsar.org/). Initially, only 9 wetlands sites in Pakistan were recognized internationally, and the number increased to 16 and 19 in 2001 and 2013, respectively (A. A. Khan & Arshad, 2014). Area-wise, the most dominant wetland types in Pakistan are the inland waters, delta marshes, mangroves, lakes and reservoirs, and man-made wetlands (fish farms, ponds, paddy fields). Out of 19 RAMSAR sites in Pakistan, 10 are in Sindh province and the majority of Sindh wetlands are marshes, mangroves, and lakes (A. A. Khan & Arshad, 2014). Also, the mangroves of the Indus delta region and Indus dolphins of the Indus wetland region are of international importance in the Sindh province f. Four major wetlands complexes are prominent in Pakistan which are the North-Western Alpine Wetlands Complex (NAWC), Salt Range Wetlands Complex (SRWC), Central Indus Wetlands Complex (CIWC), and Makran

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Coastal Wetlands Complex (MCWC) (A. A. Khan & Arshad, 2014).

Pakistan having 9.7% of the total area covered with open surface water and with 255 total wetlands of national importance, is the 11th country globally with the highest wetlands area (A. A. Khan & Arshad, 2014). Similar to other global regions, Pakistan has lost many wetland-covered areas in the past due to the over-exploitation of natural resources, diverting water flow, droughts, floods, and increased levels of industrial pollutants in the aquatic environment (Chaudhry, 2010). Relatedly, wetlands in the sub-tropical and tropical regions have also declined due to low precipitation and the conversion of existing land into agricultural land to fulfil the needs of the growing population (Salimi, Almuktar, & Scholz, 2021). Even though many conservation and restoration initiatives are taken over the past decades, the ongoing climate change is a significant threat that influences the functions of wetlands in Pakistan as it has affected the ecosystems in the country by increased temperature stress, flash floods, droughts, and changing hydrological patterns.

In the last two decades, Pakistan has taken many initiatives through international and domestic organizations to support wetlands conservation at both regional and national scales. For example, after 2000, many Non-Governmental Organizations (NGOs), and international organizations such as World Wildlife Fund (WWF) have taken conservation initiatives to sustain wetland ecosystems in Pakistan (H. Khan & Baig, 2017; Lei, 2005). Similarly, Pakistan has implemented various domestic conservation and plantation strategies such as the recent "Billion Tree Tsunami" (A. A. Khan & Arshad, 2014). As a result, some recent studies on wetlands at the local and regional levels suggest that the wetlands' situation has improved over the years (Gilani et al., 2021; Imran et al., 2021; H. Khan & Baig, 2017). However, it is notable that little effort has been put into initiatives for systematic monitoring and evaluation of spatial-temporal changes in wetland dynamics in the country. While other nations have adopted technology-based information systems for wetland monitoring and management (e.g. (Amani et al., 2019),), Pakistan still lacks an integrated national-scale monitoring mechanism to sustain wetlands as there is no national inventory available at the moment to benchmark the state of wetlands and provide information on historical changes and future simulations under environmental changes. Therefore, this area of research needs to be focused to provide information on national-scale changes in the wetlands for proper conservation, planning, and management (Chaudhry, 2010). The multi-year study of the wetlands ecosystem is among the most critical challenges that need to be addressed frequently (Salimi et al., 2021). Field surveys, water sampling, and soil sampling are costly and time-consuming tasks because of the complex nature of wetlands as well as the topographic settings of the environment where wetlands are situated (Mahdianpari, Granger, et al., 2020).

Compared with conventional field mapping techniques, Remote Sensing (RS) is a cost-effective and efficient technique used to acquire detailed spatial and temporal information about wetlands in large areas (Guo, Li, Sheng, Xu, & Wu, 2017). Due to the availability of freely accessible satellite data, researchers are more interested in the use of RS techniques for multi-temporal assessments (Asokan & Anitha, 2019). Data from optical satellites especially from Landsat (>40 years series) are useful for vegetation monitoring due to their higher revisit time (Kaplan, Yigit Avdan, & Avdan, 2019). Despite the advancement in remote sensing techniques, there are many challenges in wetland classification due to their unique characteristics (Amani, Salehi, Mahdavi, & Brisco, 2018). Some of the most highlighted problems associated with remote sensing of wetlands are higher computation requirements for large-scale studies, unavailability of data under poor weather conditions, and difficulty in differentiating individual wetland classes due to their similar spectral reflectance (Mahdianpari, Granger, et al., 2020). With the addition of new types of sensors and technological capabilities, researchers around the globe are investigating new methods, techniques, and algorithms for efficient wetlands studies (Hu, Zhang, Zhang, & Wang, 2021; Si Salah, Goldin, Rezgui, Nour El Islam, & Ait-Aoudia, 2020). The change detection technique is primarily used to monitor environmental change, deforestation, and wetland status (Hemati, Hasanlou, Mahdianpari, & Mohammadimanesh, 2021). Timely and accurate change analysis allows monitoring of wetlands conditions, state, and associated natural and/or human activities (Asokan & Anitha, 2019). Such an assessment provides potential opportunities for appropriate measures to facilitate conservation, restoration, and sustaining the wetlands.

In view of the above, this study fills the existing gap regarding national-scale long-term spatial-temporal wetland changes in Pakistan at higher resolution. For this purpose, the study first uses GEE for remote sensing data acquisition from the GEE data catalogue including Landsat archives (Landsat-5, Landsat-7, and Landsat-8) and elevation data. Then, by using a machine learning-based Random Forest (RF) algorithm, the GEE platform is used for multi-temporal classifications of wetlands at the national scale between 1990 and 2020. Lastly, geo-information-based modelling and change detection techniques are used for comparing wetlands changing patterns across the study area. Relatedly, one of the primary objectives of this study is to provide higher-resolution wetlands (swamps, marshes, and water) inventory at a national scale using open-source cloud-computing-based GEE platform, Landsat archives, RF algorithm, and GIS software. The mapping and findings on changes in wetlands over the past three decades will provide location-aware references for effective decisions and resource allocation for the restoration and conservation of wetlands—leading to wetland sustainability in Pakistan given their multiple services.

2. Materials and methods

2.1. Study area

Pakistan is situated in a tropical zone, and its climatic conditions change from low to severe temperatures. In the southern coastal region of Pakistan, the climate is primarily arid with intense monsoon rainfall and dry season with the least precipitation. Pakistan is rich in wetlands distribution and contains approximately 244 important wetlands sites (Fig. 1). Among these, 19 sites are recognized internationally by the RAMSAR convention (Fig. 1). The northern part of Pakistan is mostly above sea level, with a maximum elevation of 8.5 km. The majority of wetlands are concentrated at lower elevations and the southern part of the country, whereas the frequency of wetlands decreases with rising elevation (A. A. Khan & Arshad, 2014). According to (Chaudhry, 2010), wetlands cover roughly 10% of the total area of Pakistan and spread over an area of more than 780,000 ha as of 2010.

2.2. Data acquisition and preprocessing

2.2.1. Reference data

The primary data taken as reference material for wetlands classification are the RAMSAR site data, the entire wetland site data, and the MODIS MCD12Q1.006 LULC product data (Table 1). The 19 RAMSAR sites in Pakistan are taken as the base areas for further visualization after classification. These sites are further used to define the national-scale wetlands inventory of Pakistan. The methodology of this study involves three stages. Initially, the Landsat archive is used inside GEE and training samples are collected using high-resolution images. Secondly, classification is performed using the RF algorithm and wetlands maps are derived along with performing the accuracy assessment. Lastly, change detection is performed to analyze wetlands gain/loss trends in the last three decades (Fig. 2). Moreover, the data from the National Aeronautics and Space Administration's (NASA) Shuttle Radar Topography Mission (SRTM) are used to remove terrain shadow along with preparing a mask to remove areas with high elevation as they have a minimum frequency of wetlands.

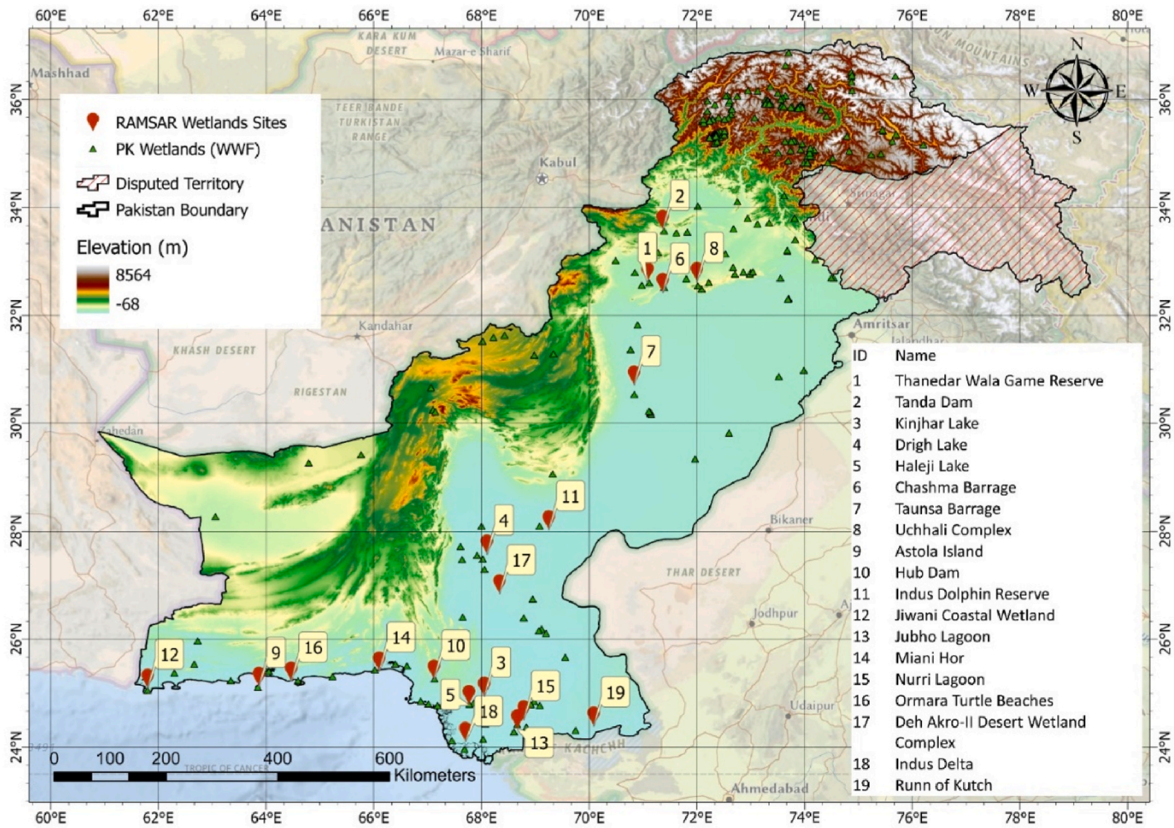

Fig. 1. Study Area map of Pakistan showing elevation, all wetland sites in Pakistan (244) and RAMSAR sites (19) geographical distribution.

Table 1
Details of different datasets used in this study.

Name	Summary	Spatial Resolution	Acquisition Date	Source
RAMSAR Pakistan Sites	Contains point locations of RAMSAR-recognized sites in Pakistan	Vector Data	2021	https://ramsar.org/
Important Pakistan Wetland Sites	Internationally important wetlands point locations in Pakistan	Vector Data	2014	https://www.gislounge.com/gis-data-worlds-wetlands/
Landsat-5 TM	Landsat-5 TM data with tier-1 processing level	30m	1990 & 2010	https://developers.google.com/earth-engine/datasets/catalog/landsat
Landsat-7 ETM	Landsat-7 ETM data with tier-1 processing level	30m	2000	
Landsat-8 OLI	Landsat-7 OLI data with tier-1 processing level	30m	2020	
SRTM DEM	Provided by NASA	30m	2000	https://developers.google.com/earth-engine/datasets/catalog/USGS_SRTMGL1_003?hl=en
Climate Data	Annual mean precipitation and temperature data for Pakistan		1990 to 2020	https://climateknowledgeportal.worldbank.org/country/pakistan

2.2.2. Google Earth Engine

The cloud-computing powered GEE is used for data acquisition, pre-processing, feature extraction, ML-based classification, and accuracy assessment (Amani et al., 2020; Waleed & Sajjad, 2022). The implementation of ML-based algorithms and deep learning modules makes this platform one of the most used tools in this decade for large-scale studies (i.e., national, regional, or global) (Hird, DeLancey, McDermid, & Kariyeva, 2017). We use the Landsat satellite data archives for this study as it is one of the longest available satellite achieves freely available in the GEE catalogue as compared with other archives (Mahdianpari, Granger, et al., 2020).

2.2.3. Landsat data availability and pre-processing

Multispectral Landsat data are taken for the multi-year classification of wetlands (Table 1). Landsat-5 Thematic Mapper (TM) images are used for 1990 and 2010, Landsat-7 Enhanced Thematic Mapper (ETM) images are used for 2000, and Landsat-8 Operational Land Imager (OLI) images are used for 2020. As seasonal images were unable to cover the entire study area (Pakistan's area > ~796,095 km^2), yearly mean composites are prepared, each representing the average wetland inundation between both wet and dry seasons of that year (Griffiths, Linden, Kuemmerle, & Hostert, 2013). Fig. 3(a) represents the path row of the satellite, and the last 30 years' annual mean precipitation and temperature patterns are shown in Fig. 3(b). Although Landsat-7 ETM data are available for the year 2010, we refrain from using it due to the "scan line error" reported after 2003 (Storey, Scaramuzza, & Schmidt, 2005). Due to induced scan line error, strips-like lines are rendered in images, affecting the quality of the acquired data (Hossain, Bujang, Zakaria, & Hashim, 2015). Previously, though many algorithms and techniques are being provided by several scholars to decrease the effect of scan line error, some distortion is still observed in resulting images (Yin, Mariethoz, Sun, & McCabe, 2017). For classification, we use bands 1–5 and 7 for Landsat-5 and Landsat-7, whereas, for Landsat-8, we use bands 1–7.

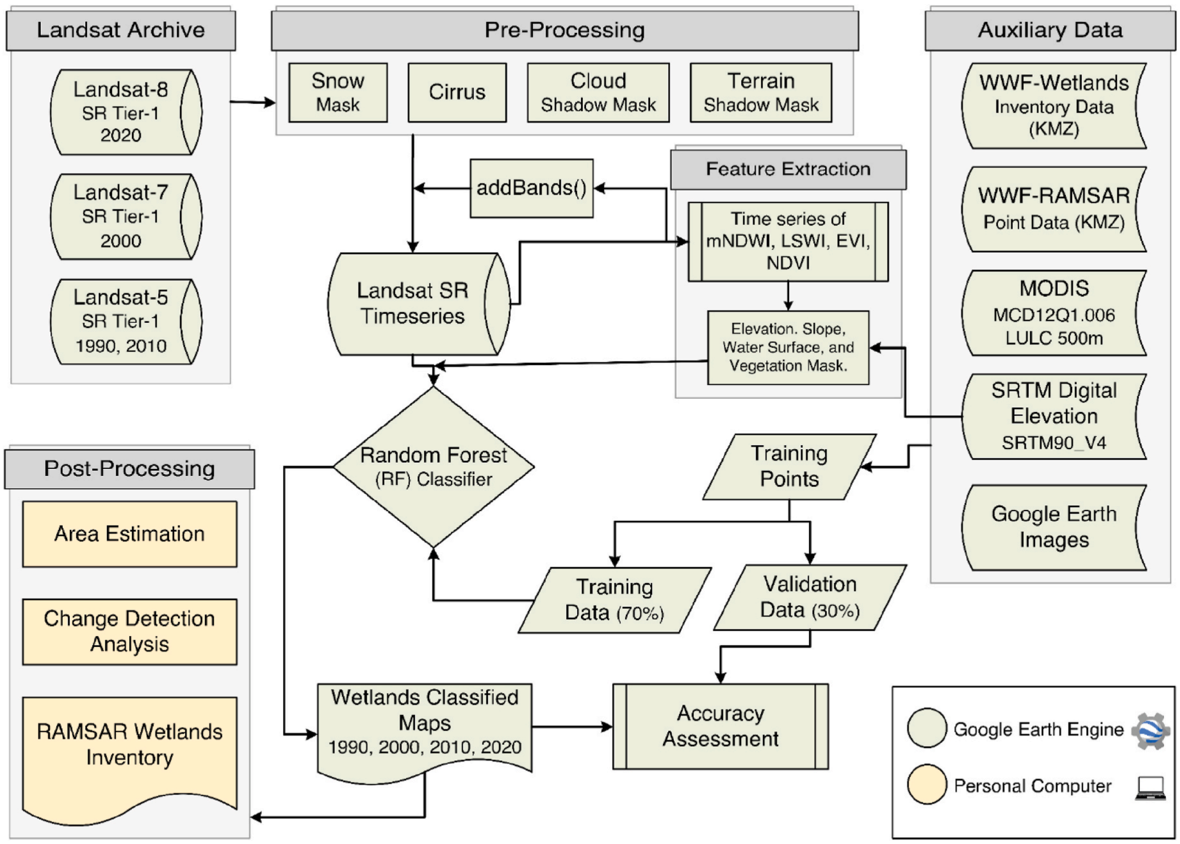

Fig. 2. Methodology flowchart adopted in this research.

For terrain shadow masking, we used the *ee.Terrain.Shadow* algorithm (available at: https://bit.ly/3HR7HBY) and masked the terrain using NASA SRTM elevation data. It is evident that wetlands are mainly observed below or near sea level (G. dong Wang, Wang, Lu, & Jiang, 2016; Yang et al., 2017). Also, some studies have reported that during the classification, snow areas might be confused with wetlands areas by the ML algorithms because of similar spectral characteristics (Gatebe & King, 2016). Therefore, to overcome this issue, we analyze RAMSAR sites' elevation and accordingly created a mask of 2500 m. Using this mask, we removed all the pixels with an elevation greater than 2500 m. As our main focus is important wetland sites only, and their distribution lies below 2500 m elevation (Fig. 1), this masking technique is effective as most of the northern mountainous areas covered with snow were filtered using this mask—resulting in improved classification.

2.3. Feature extraction

Previous researches support the use of extracted features for enhanced wetlands classification results (Mahdianpari, Granger, et al., 2020). Features such as spectral indices (SI) are extracted from the pre-processed images of Landsat-5, Landsat-7 and Landsat-8 as discussed above. Four SIs are used in this study including; 1) the Modified Normalized Difference Water Index—mNDWI (H. Xu, 2006), 2) Land Surface Water Index—LSWI (Li et al., 2013), 3) the Enhanced Vegetation Index—EVI (She et al., 2015), and 4) Normalized Difference Vegetation Index—NDVI (Townshend & Justice, 1986). NDVI is the most popular SI along with EVI. Both of these SIs are used to study vegetation dynamics. LSWI is a good SI for retrieving soil moisture-related information (Y. Wang, Zang, & Tian, 2020). Whereas, mNDWI is one of the best SI used for open surface water bodies mapping (Du et al., 2016). The modelling details of these four spectral indices are given in Equations (1)–(4), respectively.

$$NDVI = \frac{B_{nir} - B_{red}}{B_{nir} + B_{red}} \tag{1}$$

$$EVI = 2.5 \times \frac{B_{nir} - B_{red}}{B_{nir} + 6 \times B_{red} - 7.5 \times B_{blue} + 1} \tag{2}$$

$$LSWI = \frac{B_{nir} - B_{swir}}{B_{nir} + B_{swir}} \tag{3}$$

$$mNDWI = \frac{B_{green} - B_{swir}}{B_{green} + B_{swir}} \tag{4}$$

where B_{nir}, B_{red}, B_{blue}, B_{swir}, and B_{green} are near-infrared, red, blue, and shortwave-infrared bands of Landsat images.

Using the above-mentioned four SIs, a water-detecting algorithm is derived to map water surfaces with the highest possible accuracy (Du et al., 2016). The expression used for the water-detecting algorithm is given in Equation (5). Furthermore, NDVI and EVI are used together to prepare a vegetation mask using a threshold value suggested by (Mengue, Fontana, da Silva, Zanotta, & Scottá, 2019).

$$((mNDWI > EVI\ OR\ mNDWI > NDVI)\ AND\ EVI\ < 0.1) \tag{5}$$

2.4. Classification and accuracy assessment

ML-based supervised classification is performed inside GEE using the RF algorithm. Initially, the RF algorithm is fine-tuned using a parametric tuning technique, and the best-suited number of trees value is set to 115. Later, features including SI (NDVI, EVI, LSWI, and mNDWI), SRTM elevation data, vegetation, and water mask are fed to the RF classifier. For each year, classification is performed individually using each year's annual mean image and training sample points. Training samples (in the form of Global Positioning System (GPS) points) are taken using Very

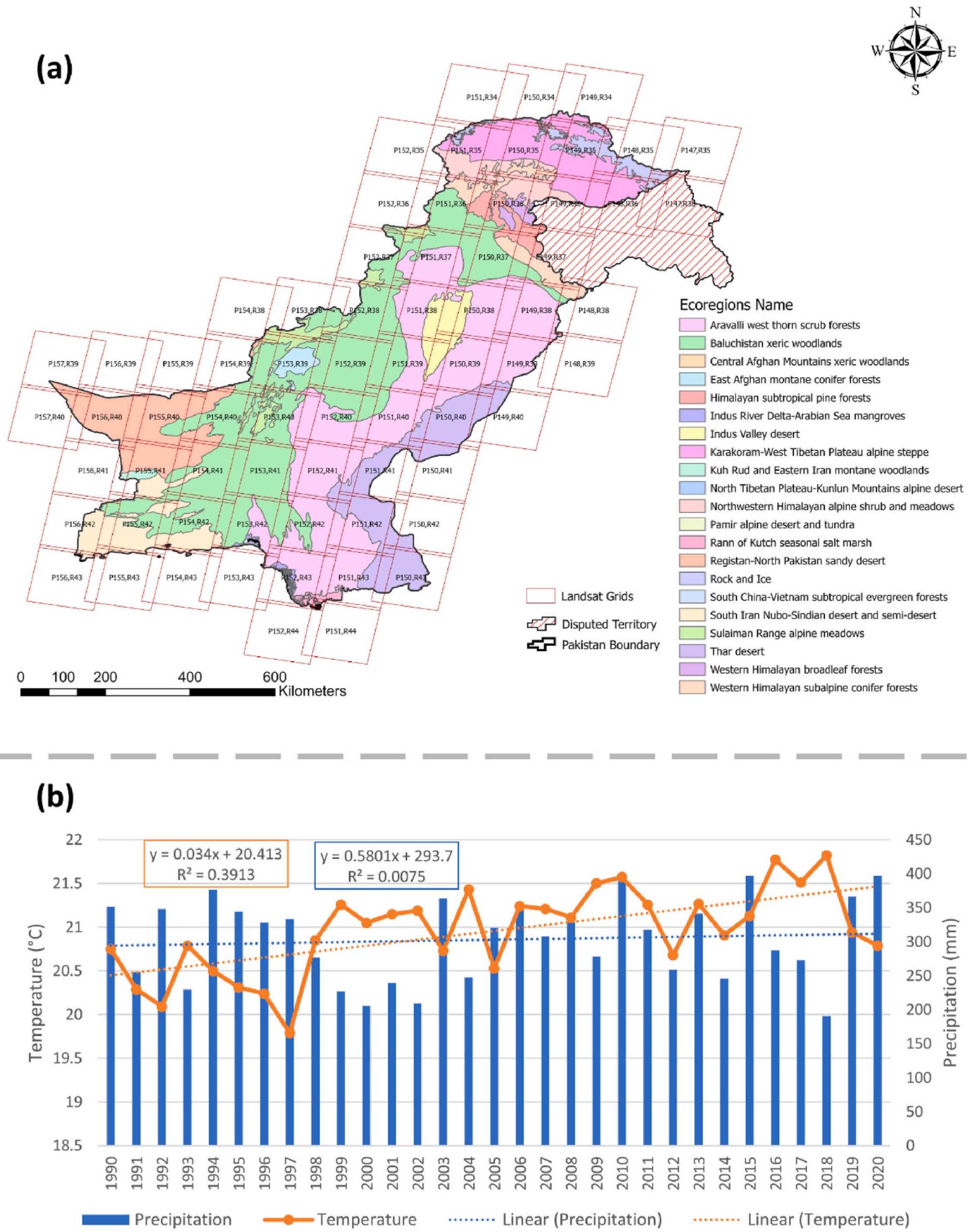

Fig. 3. Map showing (a) ecological regions of Pakistan, along with Landsat grid tiles, and Path Row information and (b) annual mean precipitation and temperature of Pakistan for the last 30 years.

High Resolution (VHR) Google Earth images, MODIS LULC product, and False Color Composite (FCC) band combination of Landsat satellite images (Fig. 2). Samples between 1000 and 3000 are taken for each class using a stratified sampling approach (Dong et al., 2020). Specifically, for collecting samples, above mentioned auxiliary remote sensing data is overlayed, and only true samples are collected through visual interpretation. Additionally, only those samples are entertained, which justify the same land-use characteristics as shown by other data sources (for example, water body in VHR Google Earth Image = water class in MODIS LULC = Water pixels in Landsat FCC images). Four land use classes including marshes, swamps, water, and others, are selected, see

Table 2
Details of different wetland types used in this study.

Name	Description
Marshes	Shallow water changes over time and contains submerged aquatic plants, grasses, brown mosses, sphagnum moss, ericaceous shrubs, and graminoids.
Swamps	Wetlands that are dominated by trees (>30%), and shrubs found in associated with other hydrological systems
Water	Open surface water that has no vegetation (lakes, ponds, rivers).
Other	All other classes except wetlands (i.e., agriculture, pasture, forest, impervious surface, barren land, desert area, and rangeland).

the description of each class in Table 2. The size of training samples is solely dependent on the area of each land use class (i.e., minimum samples are taken for the water class, whereas maximum samples are taken for "others" class). From this classification, wetlands maps are produced on a national scale from 1990 to 2020 with ten years gap interval—due to slower alteration in such LULC.

The obtained classified maps are considered reliable only when they meet some accuracy criteria. For this study, we use the Producer Accuracy (PA), User Accuracy (UA), Overall Accuracy (OA), F1-score (F1s), and Kappa Coefficient (K) as metrics to evaluate the accuracy of resultant maps (Table 3). GPS sample data is divided into 30% and 70% proportions, which are then used for validation and training respectively.

2.5. Wetlands change detection

Change detection is a technique that analyses spatial-temporal trends over a period of time. In change detection, we analyze the initial and final maps and compute the changes in wetlands. Following other researchers, we use the post-classification-based change detection technique as it analyses per-pixel change in each class over defined intervals (Baqa et al., 2021; Hemati et al., 2021). After performing the change detection, area-wise statistical analyses are performed using various area change equations. For instance, two area change equations namely Magnitude of change (MC) (Shi & Bolt, 1982), and Percent Change (PC) (Gilani et al., 2021) are computed using Equations (6) and (7), respectively. The MC represent the difference in area between two years (Equation (6)), whereas the PC represents the total area change per class per year in percent (Equation (7)). Additionally, the Annual Rate of Change (ARC) is evaluated for each class per decade using Equation (8) (Puyravaud, 2003). ARC is a statistical approach that works over the compound interest law, which evaluated a non-linear change between different year intervals, and as result, computes the rate of change in percent per given time interval (Gilani et al., 2021).

$$MC\ \left(km^2\right) = i_f - i_i \tag{6}$$

$$PC\ (\%) = \frac{i_f - i_i}{i_i} \times 100 \tag{7}$$

Table 3
Details of accuracy assessment metrics used to validate the classified maps.

Name	Summary	Formula	Justification
PA	PA is obtained by dividing the total correctly classified samples with reference sample points. Also called Recall.	$PA = \frac{tp}{tp+fn}$	Sisodia, Tiwari, and Kumar (2014)
UA	UA is obtained by dividing the total correctly classified samples by the total number of classified samples. Also called Precision.	$UA = \frac{tp}{tp+fp}$	Lyons, Keith, Phinn, Mason, and Elith (2018)
OA	Shows the proportion of total correctly classified pixels and represents the overall performance of classification.	$OA = \frac{tp+tn}{tp+tn+fp+fn}$	Lyons et al. (2018)
F1s	F1s is the harmonic mean of PA and UA and a value near 1 shows good agreement.	$2 \times \frac{tp}{tp+\frac{1}{2}(fp+fn)}$	Kampffmeyer, Salberg, and Jenssen (2016)
K	Shows degree of good agreements between classified pixel and actual pixel.	$K = \frac{p_o - p_e}{1-p_e}$	Rwanga and Ndambuki (2017)

Where tp = true positive, fn = false negative, fp = false positive, tn = true negative, p_o = observed agreement, and p_e = chance agreement.

$$ARC\ (\%) = \left(\left(\frac{1}{t_f - t_i}\right) \times \ln\left(\frac{i_f}{i_i}\right)\right) \times 100 \tag{8}$$

where i_f = area of the final image in km^2 unit, i_i = area of initial image in km^2 unit, t_f = final image acquisition year, and t_i = initial image acquisition year.

3. Results

3.1. Wetlands classification and accuracy assessment

The study results in national scale mapping of the most significant wetlands in Pakistan. The results from our mapping ascertain that the area of wetlands (swamps, marshes and water) increased in the northern and southern regions over the last 30 years (Fig. 4). The most noticeable increase is observed in swamps and marshes, which is seen from 1990 to 2000 and from 2000 to 2010.

The classified maps are validated for their accuracy using UA, PA, F1s, K, and OA, (Fig. 5). Fig. 5b–e shows the confusion matrix of the resultant wetland classified maps. The swamps and marshes area increase primarily over southern coastal areas. The accuracy assessment (Fig. 5(a)) results show a good agreement as values of K and OA are greater than 0.90 for each year. In the case of F1s, the values of each class are greater than 0.86, which further shows the authenticity of the derived wetlands classification results. It is evident that all the classes show good reliability as the maximum confusion value between the water and marshes class is observed at 10 in the year 2000 (Fig. 5(c)), while the rest of the classes have lesser false conversions.

3.2. Spatio-temporal heterogeneities in wetlands (1990–2020)

For area-wise statistical calculation, the area for each wetland class is estimated using Quantum Geographic Information System (QGIS) 3.16.7v software (www.qgis.org). The results show that the area of wetland classes shows increasing trends for the 1990–2020 period (Table 4). In 1990, the highest percentage occupying class was water, whereas in 2020 the highest percentage class is marshes. Furthermore, during the 1990–2020 interval, the area of swamps (1391.19 Km^2) and marshes (6782.23 Km^2) increased to 8510.43 Km^2, and 13904.3 Km^2, respectively. On contrary, the area of water class (8371.97 Km^2) decreased to 7818.34 Km^2. To further study the per-decade changes and spatial-temporal trends of wetlands, we performed a statistical change detection analysis.

For swamps, while the highest MC is observed in the 2000–2010 period (10522.9 km^2), the highest ARC is noted as 5.26% during 1990–2000 (Table 5). On the other hand, the lowest ARC for swamps is observed as −2.52% for the 2010–2020 decade. In the last three decades (1990–2020), the PC area of swamps increased by 511.74%. Also, the swamps show an increasing trend with 2.62% ARC during 1990–2020.

The marshes class shows the highest change during the 1999–2000 period with MC and PC equal to 5390.21 Km^2 and 79.48%, respectively (Table 5). Among the three time periods (1990–2000, 2000–2010, and 2010–2020) the highest ARC is observed during 1990–2000 (2.54%), whereas the lowest (−1.22%) is noted for the 2000–2010 period. Marshes class shows increasing trends during the past three decades (1990–2020) with MC, PC, and ARC equal to 7122.07 Km^2, 105.01%, and 1.04%, respectively. The water class shows maximum MC (3841.77 Km^2) during the 2010–2020 period, with the highest PC (33.22%) observed during the 1990–2000 period. From 1990 to 2020, the area of water shows decreasing trends with PC and ARC approximately −6.61% and −0.1%, respectively. To summarize overall, between 1990 and 2020, marshes and swamps areas increase by 105% and ~511%, respectively. For water, a decrease of ~7% in the area is observed.

Furthermore, to analyze the increasing patterns of wetlands between 1990 and 2020, we overlay the wetland classes for each year in

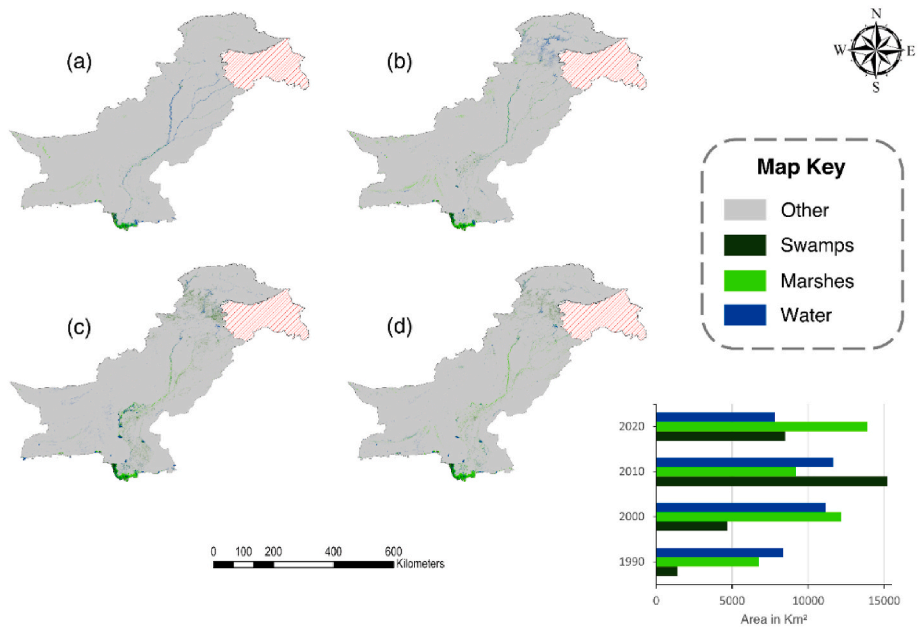

Fig. 4. Wetland classification results for (**a**) 1990, (**b**) 2000, (**c**) 2010, and (**d**) 2020 are shown along with the area distribution of each class. It is noted that the color of the area graph is consistent with the wetland classification scheme.

ascending year order (Fig. 6). The green area shows the initial base wetlands occurrence in 1990 whereas the orange, red, and blue colors represent the wetlands spread in 2000, 2010, and 2020, respectively. From the visual interpretation of Fig. 6, it is noticeable that the year 2010 (from 2000 to 2010) contributed the highest increase in the wetlands area, whereas a smaller contribution is observed in the recent decade (2010–2020). This is also evident from Table 4, that among all individual periods (1990, 2000, 2010, and 2020), the cumulative area of wetlands (marshes, swamps, and water) is greater in 2010 (36048.19 Km^2) compared with 1990 (16545.39 Km^2), 2000 (27992.49 Km^2), and 2020 (30233.06 Km^2). For inter-decedal change, wetlands considerably decrease between the 2010 to 2020 period with a −5815.12 Km^2 decrease in area (Table 5). Whereas the highest gain in the area is observed in 1990–2000 period with 11447.1 Km^2 increase in area.

Additionally, we also analyze the conversion of different wetlands classes into each other (Fig. 7(a)). These conversions are quite visible (i.e., most of the Indus Delta region (ID 18) is dominant with marshes and the majority of conversion is from water to marshes, Fig. 7(b)). Similarly, in the Miani Hor region (ID 14), the area is dominant with marshes, with the majority of conversion from other class to marshes class throughout the last 30 years.

The wetlands inventory map (Fig. 8) shows the wetlands distribution in Pakistan for the year 2020. Fig. 8 (a) shows RAMSAR and Fig. 8 (b) shows insect maps for each RAMSAR site based on wetlands classification data for 2020. Fig. 8(b) further gives a more in-depth view of the geographical distribution of swamps and marshes along lakes and coastal areas. It is observed that although Deh Akro-II Desert Wetland Complex (ID:17) was a recognized RAMSAR site, it shows the least distribution of any wetland class. This situation can further be visually confirmed and complemented by Fig. 6 represents the geographical references on the localized wetland areas which experienced a decline in terms of swamps, marshes, and water. Other than that, nearly all the RAMSAR sites have experienced a spatially varying increase in the wetlands area, and are rich in swamps and marshes proportion.

4. Discussion

Using freely available earth observation data, the GEE platform, machine-learning techniques, and geo-information modelling, this study presents the first-ever national-scale wetlands assessment in Pakistan at 30 m resolution. This initiative is in line with efforts implemented at local and national scales in different countries for effective monitoring and management of wetlands (Mahdianpari, Brisco, et al., 2020; Zhang, Xu, Li, & Li, 2022). Furthermore, this study also constructed the updated wetlands inventory of Pakistan at a national scale, which has great potential to serve the needs of a baseline for future evaluations. For instance, this baseline can be used to further evaluate the success/failures of the implemented policies at different RAMSAR sites in Pakistan.

For classification, a machine learning algorithm is preferred over conventional software-based supervised and unsupervised classification techniques because of more accurate and reliable results (Gulácsi & Kovács, 2020; Mahdianpari, Brisco, et al., 2020; Mahdianpari, Granger, et al., 2020). Among many available ML algorithms, RF is preferred because of its competitive results in wetlands classification (Guo et al., 2017). Previously, many researchers have reported a decline in accuracy when they used Landsat data alone for the classification. To comprehend this shortcoming, in this study accuracy is enhanced by integrating extracted features with Landsat data (Hemati et al., 2021), such as the utilization of imagery-based extracted features (i.e., four SIs). Future studies might also consider the utilization of much higher-resolution products and advanced tools such as LIDAR for comprehensive fine-scale mapping of the wetlands (Wu, 2017). This, however, may increase the processing and computational costs significantly when applied at a national scale, such as the one presented in this study.

4.1. *Fostering geo-information-based monitoring and management of wetlands and RAMSAR sites in Pakistan*

Remote sensing-based wetland monitoring systems are essential for the sustainable planning and management of these important sites (Ballanti, Byrd, Woo, & Ellings, 2017). The RAMSAR convention prioritizes the establishment of national wetlands inventories and information systems to address national policies for wetlands conservation in view of their multiple services. This establishment is also included as an important part of the Convention's Strategic Plan (https://www.ramsar.org/wetland/pakistan). Preparing a national scale inventory is also the main recommendation by the Global Wetlands Outlook 2018 report, which is the first report of its kind focusing on global wetlands status

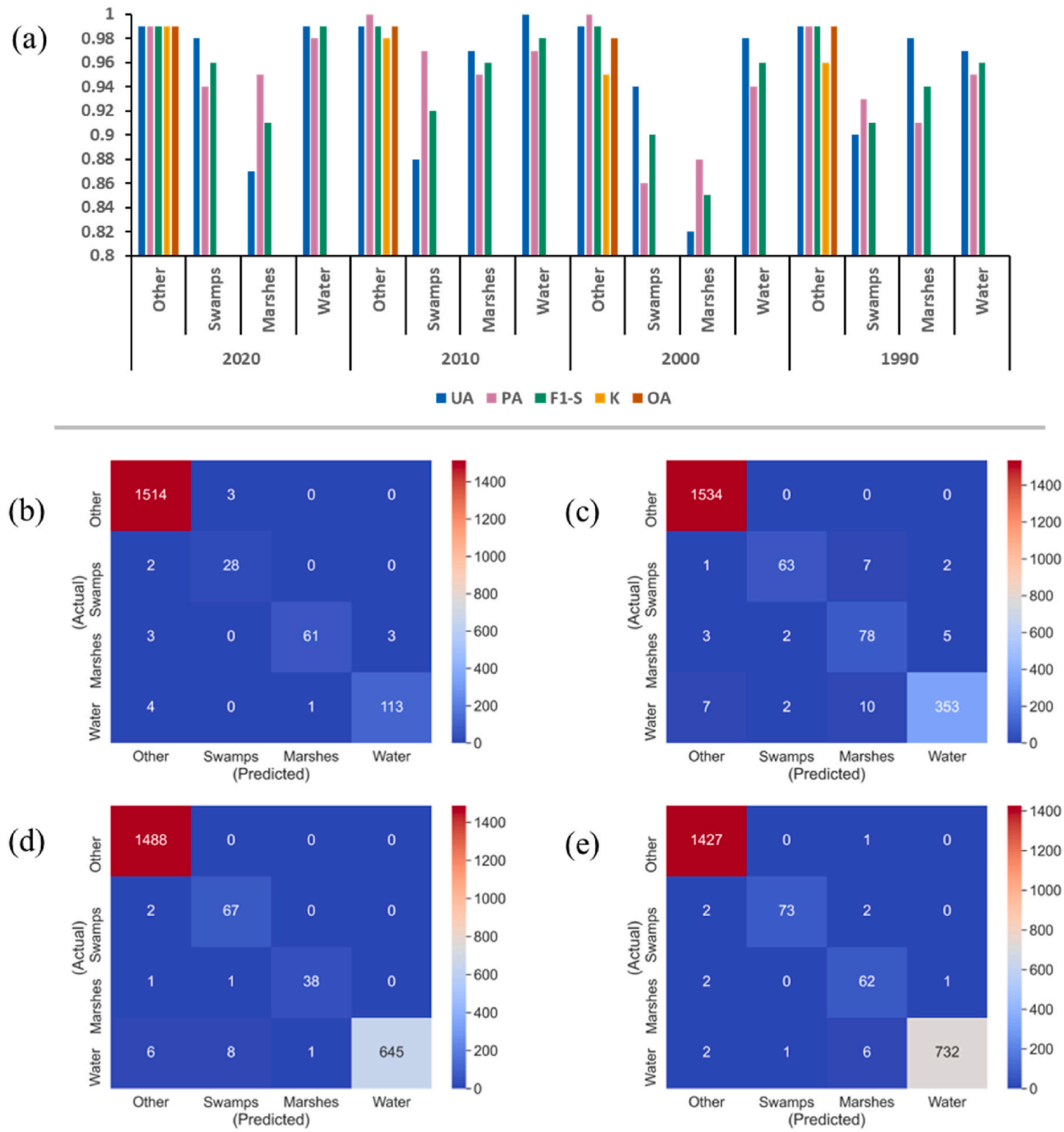

Fig. 5. (**a**) Shows the results of accuracy assessment metrics (UA, PA, F1s, K and OA) whereas confusion metrics heatmaps are shown for 1990 (**b**), 2000 (**c**), 2010 (**d**), and 2020 (**e**).

Table 4
Area distribution of different wetland classes (1990–2020). It is noted that Area (%) represents the percentage of wetland class in that year out of total area in a particular year.

Wetland Class	1990		2000		2010		2020	
	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
Swamps	1391.19	8.41	4666.92	16.67	15189.82	42.14	8510.43	28.15
Marshes	6782.23	40.99	12172.44	43.48	9198.26	25.52	13904.3	45.99
Water	8371.97	50.6	11153.13	39.84	11660.11	32.35	7818.34	25.86
Total Area	16545.39		27992.49		36048.19		30233.06	

(https://www.global-wetland-outlook.ramsar.org/). In this regard, the World-Wide Fund for Nature (WWF) (http://wwf.org.pk) has played a huge role in wetlands management and conservation in Pakistan. WWF in collaboration with the Ministry of Environment-Pakistan, partially funded by the United Nations Development Programme, initiated a Pakistan Wetlands Survey Program (PWP) in 2004 (Qamer et al., 2009, pp. 307–310). Though this program prioritizes the establishment of a national-scale GIS-based wetlands inventory (PWG) to monitor and provide references for decision-making in support of wetlands conservation and restoration in the country, no such platform has yet been

Table 5
Area-wise percentage distribution and percent change of different wetland classes (1990–2020).

Wetland Class	1990–2000			2000–2010			2010–2020			1990–2020		
	MC (Km^2)	PC (%)	ARC (%)	MC (Km^2)	PC (%)	ARC (%)	MC (Km^2)	PC (%)	ARC (%)	MC (Km^2)	PC (%)	ARC (%)
Swamps	3275.73	235.46	5.26	10522.9	225.48	5.13	−6679.39	−43.97	−2.52	7119.23	511.74	2.62
Marshes	5390.21	79.48	2.54	−2974.18	−24.43	−1.22	4706.04	51.16	1.79	7122.07	105.01	1.04
Water	2781.16	33.22	1.25	506.98	4.55	0.19	−3841.77	−32.95	−1.74	−553.63	−6.61	−0.1
Total	11447.1			8055.7			−5815.12			13687.67		

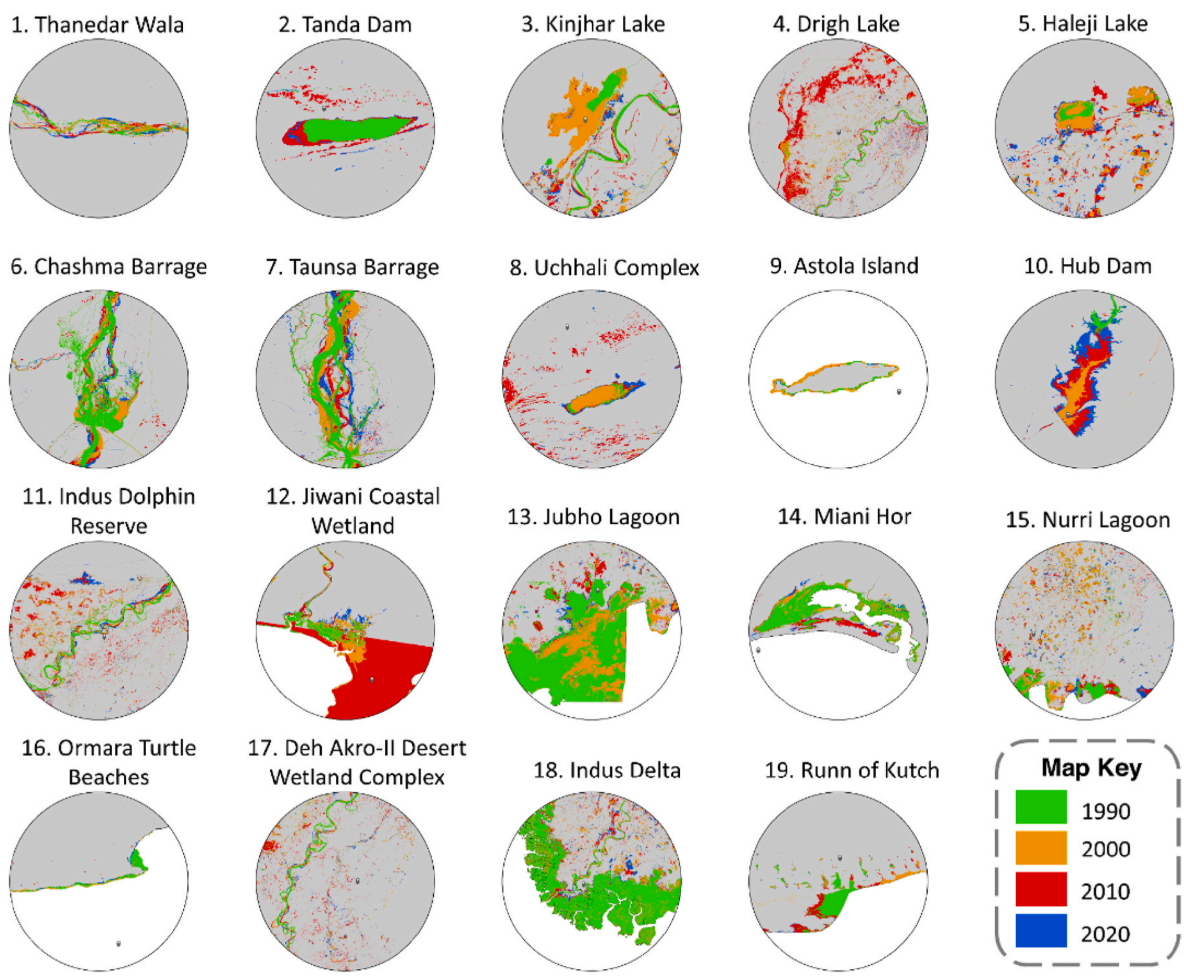

Fig. 6. Wetlands trends over Pakistan RAMSAR sites for 1990, 2000, 2010, and 2020.

established and made public. In Pakistan, though there are some governmental bodies working on the conservation of wetlands, the availability of multi-temporal wetlands inventory data with the adequate spatial resolution is still insufficient. Thus, this study is particularly important to fill this gap by developing an up-to-date inventory of wetlands in Pakistan using 30 m resolution Landsat time series data and ML-based RF algorithm inside GEE (Fig. 8).

The spatial-temporal assessment results presented here advance our understanding regarding the state of wetlands in Pakistan, which has important implications to design appropriate measures and action plans for the conservation and restoration of wetlands—especially RAMSAR sites—in the face of anthropogenic activities (A. A. Khan & Arshad, 2014; Şimşek & Ödül, 2018). Pakistan has severely been affected due to climate change-induced flooding and is particularly vulnerable to global warming (Masson-Delmotte, V. et al., 2021). Wetlands are well recognized for their ability to mitigate flood impacts due to their sponge-like nature that traps and then slowly releases the surface water, thus improving the overall resilience (Hauser et al., 2017; Sajjad, 2021). Similarly, wetlands also play an important role to mitigate global warming as wetlands sequester carbon from the atmosphere. Additionally, the inventory is also useful to quantify the spatial-temporal dynamics of several services provided by wetlands including flood protection, carbon storage, and economic incentives—left for future studies.

Though there are no studies at hand to compare our large-scale and higher-resolution spatial-temporal assessment of Pakistan's wetlands, the increasing trends in the wetlands of Pakistan as identified in our study are in line with some local studies (Ahmad & Erum, 2012; Gilani et al., 2021). For example, Gilani (2021) performed a study on only mangroves in 5 main regions of Pakistan and found an overall increasing pattern in the mangrove area. Their study revealed a ~3% increase in each mangrove site (Indus Delta, Sonmiani Khor, Kalmat Khor, and Jiwani) in Pakistan (except the Sandspit site, which has only a 0.3% increase). Another study from Ahmad and Erum (2012) evaluated

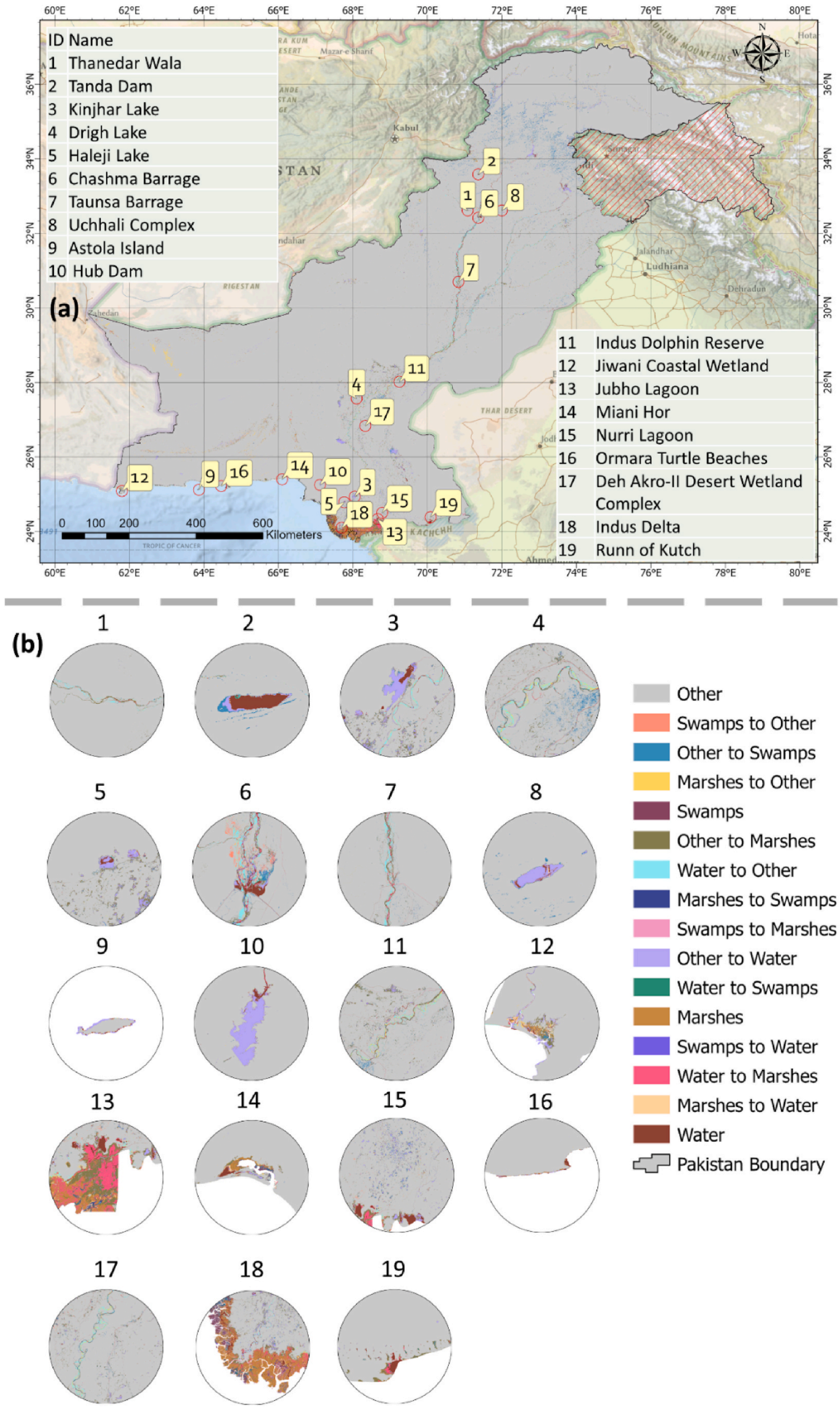

Fig. 7. (**a**) National scale conversion map of different wetlands classes during the 1990 to 2020 period, (**b**) site-level conversion maps for each respective RAMSAR site.

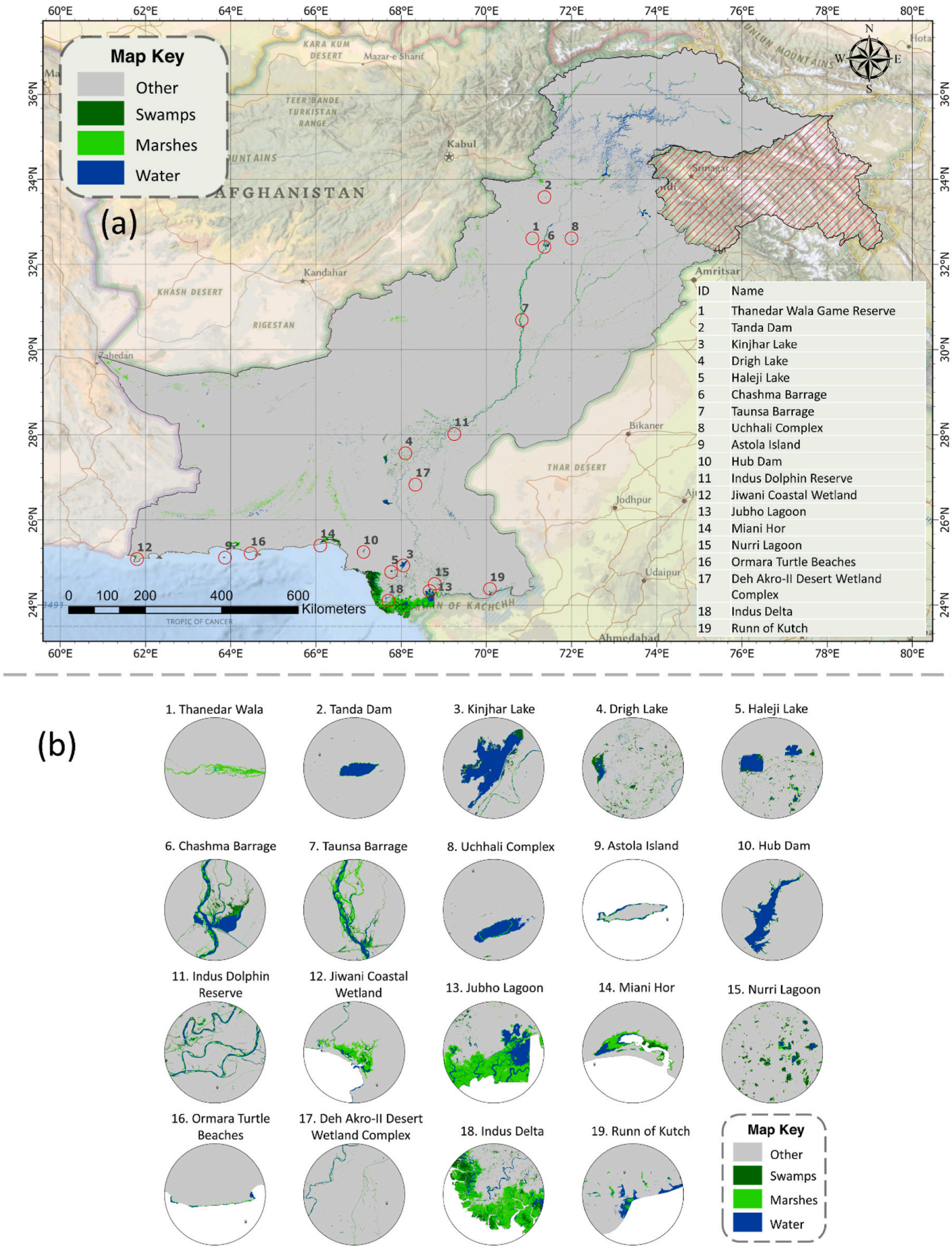

Fig. 8. Final wetlands inventory map showing (**a**) Geographic distribution of national level wetlands in Pakistan updated till 2020 and (b) site level state of wetlands highlights over RAMSAR sites as of 2020.

wetland change in the Kallar Kahar region of Pakistan using Quick bird and Corona satellite imagery with object-based image classification techniques for 1972 and 2008. Their study also revealed an increase of 40% in wetlands (waterbody class). Thus both of these studies justify the improving trends of wetlands in different localized regions of Pakistan.

The improvements seen in wetlands dynamics over the years are attributed to different conservation campaigns (started after 2006) by national and international Non-governmental Organizations, the Pakistan Navy, the Government of Pakistan, and Community-Based Organizations (A. A. Khan & Arshad, 2014). As a result, Pakistan was added to the Guinness Book of World Records after the plantation of ~0.85 million mangrove saplings in the Indus delta site within 24 h (Gilani et al., 2021). However, the effectiveness of such initiatives requires proper monitoring and management, both spatially and temporally, through advanced yet cost-effective means, such as the one presented in this study (i.e., through the integration of machine learning, remote sensing, and geo-information models). While the wetlands showed improvements in our study, in 2010, a loss of −5815.12 Km^2 is prominent. Previous studies conclude that urbanization and agriculture are the major causes of wetlands loss (Mao et al., 2018). In Pakistan, this loss may be due to agriculture as indicated in the agricultural report for 2020-21 (available at www.finance.gov.pk). According to this, since 2015, rice production has increased up to 70% in the region, where most rice is grown in the flooded soils of Punjab.

4.2. Limitations and the way forward

The main hurdle behind the wetlands mapping at the national scale was the lack of field samples for the classification of different wetlands classes. This was primarily due to a lack of survey data and poor management of wetlands sites in many parts of the country. Another limitation associated with this study is the unavailability of free high-resolution satellite data (i.e., SPOT), which could further enable the assessment on a much higher resolution than the one presented here (i.e., 30 m). Similarly, future studies might also consider employing object-based image analysis (OBIA) for classification, which was not feasible in our case due to low computational power and large-scale assessment (i.e., national level). Under such circumstances, Landsat archives and pixel-based classification techniques are the best options to analyze the dynamics of the spatial-temporal wetlands at 30 m resolution on a large geographical area. Using this study as a baseline, future studies might focus on providing higher-resolution wetlands inventory, OBIA-based classification to study wetlands dynamics over regional areas, and integrating multispectral and Synthetic Aperture Radar-based instruments for studying wetlands.

It is notable that the maximum confusion is observed between water with marshes and marshes with swamps classes (Fig. 5). This issue has also been highlighted by many other researchers. They highlighted that when a pixel-based approach with medium-resolution satellite data (i.e., Landsat data) is being used, accuracy decreases because of similar spectral patterns of marshes and other wetland classes (Adam, Mutanga, & Rugege, 2010; Amani et al., 2018; Amler, Schmidt, & Menz, 2015; Gatebe & King, 2016; Hird et al., 2017). For example (Amani et al., 2018), compared the spectral reflectance of various wetlands classes with different optical instruments. They also observed that fens, bogs, marshes, and swamps show similar spectral behaviour. Hence, while such observation in our study is in line with the literature, it further calls for additional research to mitigate such issues as well as the adoption of higher-resolution data. Doing so, however, may result in increased computational and financial costs, which may not be feasible for developing countries like Pakistan.

5. Conclusions

This study evaluates the current state and historical spatial-temporal changes in wetlands (swamps, marshes, and water) in Pakistan from 1990 to 2020 based on an inter-decadal comparison. For this purpose, machine learning, cloud-computing platform, and geo-information models are employed. The applied methodology is efficient as it utilized a features extraction technique with a conventional machine learning RF algorithm. Also, the study performed is cost-effective as the GEE cloud computing platform is utilized in this study to classify the wetlands at a national scale, and the data used are freely available. In general, there has been an increase in most of the wetland areas, with some geographical areas facing losses in terms of wetlands. In the context of the sustainability of wetlands in Pakistan, the first-of-its-kind national-level wetland inventory is established providing long-term spatial-temporal state of different wetlands—providing important references for conservation and restoration-related management practices.

The results presented here are of particular importance to act as a baseline for future assessments and can help evaluate the effectiveness of conservation and restoration policies in Pakistan. Furthermore, the wetlands' distribution data produced on a national scale is of particular interest to researchers, modelers, and stakeholders to advance the assessment and monitoring of wetlands in Pakistan along with further quantification of diverse services provided by these wetlands. Hence, this study could potentially act as a baseline to understand the historical spatial-temporal dynamics of wetland services as well as simulate future predictions in the face of environmental changes (i.e., climate change and rapid urbanization, etc.).

Conclusively, the results from this study can be used to update the existing national wetlands database and will provide further insights for studying individual RAMSAR sites in Pakistan to quantify their multiple services in the context of national resource evaluation and management.

Author contributions

Conceptualization, A.S. and S.C.; ***Methodology/Software/Validation***, A.S., M.W., M.S.; ***Formal Analysis***, A.S., M.W.; ***Investigation***, A.S. and S.C.; ***Resources/Data Curation***, A.S.; ***writing—original draft preparation***, M.W., A.S., M.S.; ***Writing—review and editing***, M.S. A.S. and S.C.; ***Visualization***, M.S., M.W.; ***Supervision***, S.C. and M.S.; ***Project administration***, S.C.; Funding ***Acquisition***, S.C. All authors have read and agreed to the published version of the manuscript.

Data availability statement

The data used in this study are open access and all the data sources are provided in this paper. The classified wetland maps are available from the corresponding authors.

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References

Adam, E., Mutanga, O., & Rugege, D. (2010). Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review. *Wetlands Ecology and Management, 18*(3), 281–296. https://doi.org/10.1007/s11273-009-9169-z

Ahmad, S. S., & Erum, S. (2012). Remote sensing and GIS application in wetland change analysis: Case study of Kallar Kahar. *Science, Technology and Development, 31*(3), 251–259.

Amani, M., Brisco, B., Afshar, M., Mirmazloumi, S. M., Mahdavi, S., Mirzadeh, S. M. J., et al. (2019). A generalized supervised classification scheme to produce provincial wetland inventory maps: An application of google earth engine for big geo data processing. *Big Earth Data, 3*(4), 378–394. https://doi.org/10.1080/20964471.2019.1690404

Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., et al. (2020). Google earth engine cloud computing platform for remote sensing big data applications: A comprehensive review. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13*, 5326–5350. https://doi.org/10.1109/JSTARS.2020.3021052

Amani, M., Salehi, B., Mahdavi, S., & Brisco, B. (2018). Spectral analysis of wetlands using multi-source optical satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing, 144*(January), 119–136. https://doi.org/10.1016/j.isprsjprs.2018.07.005

Amler, E., Schmidt, M., & Menz, G. (2015). Definitions and mapping of East African Wetlands: A review. *Remote Sensing, 7*(5), 5256–5282. https://doi.org/10.3390/rs70505256

Asokan, A., & Anitha, J. (2019). Change detection techniques for remote sensing applications: A survey. *Earth Science Informatics, 12*(2), 143–160. https://doi.org/10.1007/s12145-019-00380-5

Ballanti, L., Byrd, K. B., Woo, I., & Ellings, C. (2017). Remote sensing for wetland mapping and historical change detection at the Nisqually River Delta. *Sustainability, 9*(11), 1919. https://doi.org/10.3390/su9111919

Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., et al. (2021). Monitoring and modeling the patterns and trends of urban growth using urban sprawl matrix and CA-Markov model: A case study of Karachi, Pakistan. *Land, 10*(7). https://doi.org/10.3390/land10070700

Chaudhry, A. A. (2010). Wetlands in Pakistan : What is happening to them. *Environment: Science and Policy for Sustainable Development, 5*(June), 49–70.

Dong, S., Chen, Z., Gao, B., Guo, H., Sun, D., & Pan, Y. (2020). Stratified even sampling method for accuracy assessment of land use/land cover classification: A case study of Beijing, China. *International Journal of Remote Sensing, 41*(16), 6427–6443. https://doi.org/10.1080/01431161.2020.1739349

Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W., & Li, X. (2016). Water bodies' mapping from Sentinel-2 imagery with Modified Normalized Difference Water Index at 10-m spatial resolution produced by sharpening the swir band. *Remote Sensing, 8*(4), 354. https://doi.org/10.3390/rs8040354

Gatebe, C. K., & King, M. D. (2016). Airborne spectral BRDF of various surface types (ocean, vegetation, snow, desert, wetlands, cloud decks, smoke layers) for remote sensing applications. *Remote Sensing of Environment, 179*, 131–148. https://doi.org/10.1016/j.rse.2016.03.029

Gilani, H., Naz, H. I., Arshad, M., Nazim, K., Akram, U., Abrar, A., et al. (2021). Evaluating mangrove conservation and sustainability through spatiotemporal (1990–2020) mangrove cover change analysis in Pakistan. *Estuarine, Coastal and Shelf Science, 249*, Article 107128. https://doi.org/10.1016/j.ecss.2020.107128. June 2020.

Griffiths, P., van der Linden, S., Kuemmerle, T., & Hostert, P. (2013). A pixel-based landsat compositing algorithm for large area land cover mapping. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6*(5), 2088–2101. https://doi.org/10.1109/JSTARS.2012.2228167

Gulácsi, A., & Kovács, F. (2020). Sentinel-1-imagery-based high-resolutionwater cover detection on wetlands, aided by google earth engine. *Remote Sensing, 12*(10), 1–20. https://doi.org/10.3390/rs12101614

Guo, M., Li, J., Sheng, C., Xu, J., & Wu, L. (2017). A review of wetland remote sensing. *Sensors, 17*(4), 777. https://doi.org/10.3390/s17040777

Hauser, L. T., Nguyen Vu, G., Nguyen, B. A., Dade, E., Nguyen, H. M., Nguyen, T. T. Q., et al. (2017). Uncovering the spatio-temporal dynamics of land cover change and fragmentation of mangroves in the Ca Mau peninsula, Vietnam using multi-temporal SPOT satellite imagery (2004–2013). *Applied Geography, 86*, 197–207. https://doi.org/10.1016/j.apgeog.2017.06.019

Hemati, M., Hasanlou, M., Mahdianpari, M., & Mohammadimanesh, F. (2021). A systematic review of landsat data for change detection applications: 50 years of monitoring the earth. *Remote Sensing, 13*(15), 2869. https://doi.org/10.3390/rs13152869

Hird, J. N., DeLancey, E. R., McDermid, G. J., & Kariyeva, J. (2017). Google earth engine, open-access satellite data, and machine learning in support of large-area probabilisticwetland mapping. *Remote Sensing, 9*(12), 1315. https://doi.org/10.3390/rs9121315

Hossain, M. S., Bujang, J. S., Zakaria, M. H., & Hashim, M. (2015). Assessment of Landsat 7 Scan Line Corrector-off data gap-filling methods for seagrass distribution mapping. *International Journal of Remote Sensing, 36*(4), 1188–1215. https://doi.org/10.1080/01431161.2015.1007257

Hu, X., Zhang, P., Zhang, Q., & Wang, J. (2021). Improving wetland cover classification using artificial neural networks with ensemble techniques. *GIScience and Remote Sensing, 58*(4), 603–623. https://doi.org/10.1080/15481603.2021.1932126

Imran, H. M., Hossain, A., Islam, A. K. M. S., Rahman, A., Bhuiyan, M. A. E., Paul, S., et al. (2021). Impact of land cover changes on land surface temperature and human thermal comfort in Dhaka city of Bangladesh. *Earth Systems and Environment, 5*(3), 667–693. https://doi.org/10.1007/s41748-021-00243-4

Kampffmeyer, M., Salberg, A. B., & Jenssen, R. (2016). Semantic segmentation of small objects and modeling of uncertainty in urban remote sensing images using deep convolutional neural networks. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 680. https://doi.org/10.1109/CVPRW.2016.90. –688.

Kaplan, G., Yigit Avdan, Z., & Avdan, U. (2019). Mapping and monitoring wetland dynamics using thermal, optical, and SAR remote sensing data. *Wetlands Management - Assessing Risk and Sustainable Solutions, 87*. https://doi.org/10.5772/intechopen.80264

Khan, A. A., & Arshad, S. (2014). Wetlands of Pakistan : Distribution , degradation and management. *Pakistan Geographical Review, 69*(1), 28–45.

Khan, H., & Baig, S. (2017). High altitude wetlands of the HKH region of northern Pakistan – status of current knowledge, challenges and research opportunities. *Wetlands, 37*(2), 371–380. https://doi.org/10.1007/s13157-016-0868-y

Lei, G. (2005). *Review of the himalayan wetlands conservation initiative*. Asia Regional Meeting in Preparation for Ramsar COP9. May, 13–16.

Li, W., Du, Z., Ling, F., Zhou, D., Wang, H., Gui, Y., et al. (2013). A comparison of land surface water mapping using the normalized difference water index from TM, ETM+ and ALI. *Remote Sensing, 5*(11), 5530–5549. https://doi.org/10.3390/rs5115530

Liu, X., Dong, G., Wang, X., Xue, Z., Jiang, M., Lu, X., et al. (2013). Characterizing the spatial pattern of marshlands in the Sanjiang plain, Northeast China. *Ecological Engineering, 53*, 335–342. https://doi.org/10.1016/j.ecoleng.2012.12.071

Lyons, M. B., Keith, D. A., Phinn, S. R., Mason, T. J., & Elith, J. (2018). A comparison of resampling methods for remote sensing classification and accuracy assessment. *Remote Sensing of Environment, 208*, 145–153. https://doi.org/10.1016/j.rse.2018.02.026

Mahdianpari, M., Brisco, B., Granger, J. E., Mohammadimanesh, F., Salehi, B., Banks, S., et al. (2020). The second generation Canadian wetland inventory map at 10 meters resolution using google earth engine. *Canadian Journal of Remote Sensing, 46*(3), 360–375. https://doi.org/10.1080/07038992.2020.1802584

Mahdianpari, M., Granger, J. E., Mohammadimanesh, F., Salehi, B., Brisco, B., Homayouni, S., et al. (2020). Meta-analysis of wetland classification using remote sensing: A systematic review of a 40-year trend in North America. *Remote Sensing, 12*(11). https://doi.org/10.3390/rs12111882

Mao, D., Luo, L., Wang, Z., Wilson, M. C., Zeng, Y., Wu, B., et al. (2018). Conversions between natural wetlands and farmland in China: A multiscale geospatial analysis. *Science of the Total Environment, 634*, 550–560. https://doi.org/10.1016/j.scitotenv.2018.04.009

Masson-Delmotte, V., P., Zhai, A., Pirani, S. L., Connors, C., Péan, S., Berger, N., et al. (2021). The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change, 2021 *In Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*, 1979. August https://www.ipcc.ch/report/ar6/wg1/#FullReport%0Ahttps://www.ipcc.ch/report/ar6/wg1/%0Ahttps://www.ipcc.ch/report/ar6/wg1/%0Ahttps://www.ipcc.ch/report/ar6/wg1/%0Ahttps://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Headline_Statements.pdf.

Mengue, V. P., Fontana, D. C., da Silva, T. S., Zanotta, D., & Scottá, F. C. (2019). Methodology for classification of land use and vegetation cover using MODIS-EVI data. *Revista Brasileira de Engenharia Agrícola e Ambiental, 23*(11), 812–818. https://doi.org/10.1590/1807-1929/agriambi.v23n11p812-818

Puyravaud, J. P. (2003). Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management, 177*(1–3), 593–596. https://doi.org/10.1016/S0378-1127(02)00335-3

Qamer, F. M., Ashraf, M. S., Hussain, N., Saleem, R., Ali, H., Mirza, H., et al. (2009). *Pakistan Wetlands GIS - a multi-scale national wetlands inventory*. Proceedings, 33rd International Symposium on Remote Sensing of Environment, ISRSE, 2009.

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy assessment of land use/land cover classification using remote sensing and GIS. *International Journal of Geosciences*, 611–622. https://doi.org/10.4236/ijg.2017.84033, 08(04.

Sajjad, M. (2021). Disaster resilience in Pakistan: A comprehensive multi-dimensional spatial profiling. *Applied Geography, 126*. https://doi.org/10.1016/j.apgeog.2020.102367

Salimi, S., Almuktar, S. A. A. A. N., & Scholz, M. (2021). Impact of climate change on wetland ecosystems: A critical review of experimental wetlands. *Journal of Environmental Management, 286*, Article 112160. https://doi.org/10.1016/j.jenvman.2021.112160

She, X., Zhang, L., Cen, Y., Wu, T., Huang, C., & Baig, M. H. A. (2015). Comparison of the continuity of vegetation indices derived from Landsat 8 OLI and Landsat 7 ETM+ data among different vegetation types. *Remote Sensing, 7*(10), 13485–13506. https://doi.org/10.3390/rs71013485

Shi, Y., & Bolt, B. A. (1982). The standard error of the magnitude-frequency b value. *Bulletin of the Seismological Society of America, 72*(5), 1677–1687. https://doi.org/10.1785/bssa0720051677

Si Salah, H., Goldin, S. E., Rezgui, A., Nour El Islam, B., & Ait-Aoudia, S. (2020). What is a remote sensing change detection technique? Towards a conceptual framework. *International Journal of Remote Sensing, 41*(5), 1788–1812. https://doi.org/10.1080/01431161.2019.1674463

Şimşek, Ç. K., & Ödül, H. (2018). Investigation of the effects of wetlands on micro-climate. *Applied Geography, 97*, 48–60.

Sisodia, P. S., Tiwari, V., & Kumar, A. (2014). *Analysis of supervised maximum likelihood classification for remote sensing image* (pp. 1–4). International Conference on Recent Advances and Innovations in Engineering. https://doi.org/10.1109/ICRAIE.2014.6909319. ICRAIE 2014.

Storey, J., Scaramuzza, P., & Schmidt, G. (2005). Landsat 7 scan line corrector off-gap filled product development. *Proceeding of Pecora, 16*, 23–27.

Townshend, J. R. G., & Justice, C. O. (1986). Analysis of the dynamics of african vegetation using the normalized difference vegetation index. *International Journal of Remote Sensing, 7*(11), 1435–1445. https://doi.org/10.1080/01431168608948946

Waleed, M., & Sajjad, M. (2022). Leveraging cloud-based computing and spatial modeling approaches for land surface temperature disparities in response to land cover change: Evidence from Pakistan. *Remote Sensing Applications: Society and Environment, 25*(November 2021), Article 100665. https://doi.org/10.1016/j.rsase.2021.100665

Wang, G. dong, Wang, M., Lu, X. guo, & Jiang, M. (2016). Surface elevation change and susceptibility of coastal wetlands to sea level rise in Liaohe Delta, China. *Estuarine, Coastal and Shelf Science, 180*, 204–211. https://doi.org/10.1016/j.ecss.2016.07.011

Wang, Y., Zang, S., & Tian, Y. (2020). Mapping paddy rice with the random forest algorithm using MODIS and SMAP time series. *Chaos, Solitons & Fractals, 140*, Article 110116. https://doi.org/10.1016/j.chaos.2020.110116

Wu, Q. (2017). GIS and remote sensing applications in wetland mapping and monitoring. *Comprehensive Geographic Information Systems, 3*, 140–157. https://doi.org/10.1016/B978-0-12-409548-9.10460-9

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing, 27*(14), 3025–3033. https://doi.org/10.1080/01431160600589179

Xu, X., Chen, M., Yang, G., Jiang, B., & Zhang, J. (2020). Wetland ecosystem services research: A critical review. *Global Ecology and Conservation, 22*, Article e01027. https://doi.org/10.1016/j.gecco.2020.e01027

Xu, T., Weng, B., Yan, D., Wang, K., Li, X., Bi, W., et al. (2019). Wetlands of international importance: Status, threats, and future protection. *International Journal of Environmental Research and Public Health, 16*(10), 1818. https://doi.org/10.3390/ijerph16101818

Yang, S., Liebner, S., Winkel, M., Alawi, M., Horn, F., Dörfer, C., et al. (2017). In-depth analysis of core methanogenic communities from high elevation permafrost-affected wetlands. *Soil Biology and Biochemistry, 111*, 66–77. https://doi.org/10.1016/j.soilbio.2017.03.007

Yin, G., Mariethoz, G., Sun, Y., & McCabe, M. F. (2017). A comparison of gap-filling approaches for landsat-7 satellite data. *International Journal of Remote Sensing, 38* (23), 6653–6679. https://doi.org/10.1080/01431161.2017.1363432

Zhang, Z., Xu, N., Li, Y., & Li, Y. (2022). Sub-continental-scale mapping of tidal wetland composition for East Asia: A novel algorithm integrating satellite tide-level and phenological features. *Remote Sensing of Environment, 269*. https://doi.org/10.1016/j.rse.2021.112799. June 2021.