forests

Article

Quantitative Assessment of Deforestation and Forest Degradation in Margalla Hills National Park (MHNP): Employing Landsat Data and Socio-Economic Survey

Hiba Ahmed [1], Hamayoon Jallat [1], Ejaz Hussain [2], Najam u Saqib [1], Zafeer Saqib [3], Muhammad Fahim Khokhar [1,*] and Waseem Razzaq Khan [4,*]

[1] Institute of Environmental Science and Engineering, National University of Science and Technology, Islamabad 44000, Pakistan
[2] Department of Social Sciences, Lahore School of Economics, Lahore 53200, Pakistan
[3] Department of Environmental Science, International Islamic University Islamabad, Islamabad 44000, Pakistan
[4] Department of Forestry Science, Universiti Putra Malaysia Kampus, Bintulu 97008, Malaysia
* Correspondence: fahim.khokhar@iese.nust.edu.pk (M.F.K.); khanwaseem@upm.edu.my (W.R.K.); Tel.: +92-51-9085-4308 (M.F.K.)

Abstract: Deforestation and forest degradation is a global concern, especially in developing countries. The Margalla Hills of Pakistan—Himalayan foothills—also face the threat of deforestation and forest degradation. These Margalla Hills, considering the need for forest protection activities in Pakistan, were declared a reserved national forest and named "the Margalla Hills National Park (MHNP)". This study quantitively evaluates whether deforestation and forest degradation have occurred at MHNP and identifies their possible drivers. Satellite (Landsat) data 1988–2020 was employed for the land use change analysis, whereas a socio-economic survey of the local population and structured interviews with government officials were conducted to identify the drivers of deforestation. Supervised classification was performed for imagery classification and the Vegetation Condition Index (VCI) was also calculated to measure degradation. Supervised classification showed that the forest cover increased from 65% of the total area in 1988 to 69% in 2020. The VCI results show that the moderate level of degradation has increased from 3.5% of MHNP area in 1988 to 8.8% in 2020. The cumulative measure of degradation from 1988 to 2020 is 1.09% of the total forest (using $p < 0.05$). Major drivers identified are fuel wood and timber collection. The results reveal a decline in both deforestation and forest degradation. There is a need for further quantitative analysis of the drivers, strict implementation of legislative and control measures, and continuous invigilation of the deforestation trends in MHNP.

Keywords: deforestation; environmental degradation; climate change; MHNP; Margalla hills; public policy

check for updates

Citation: Ahmed, H.; Jallat, H.; Hussain, E.; Saqib, N.u.; Saqib, Z.; Khokhar, M.F.; Khan, W.R. Quantitative Assessment of Deforestation and Forest Degradation in Margalla Hills National Park (MHNP): Employing Landsat Data and Socio-Economic Survey. *Forests* **2023**, *14*, 201. https://doi.org/10.3390/f14020201

Academic Editor: Steven L. Petersen

Received: 30 November 2022
Revised: 1 January 2023
Accepted: 16 January 2023
Published: 20 January 2023

1. Introduction

The importance of forests is incontrovertible considering their environmental and socio-economic advantages [1,2]. They provide various ecosystem services such as carbon sequestration, water regulation, and climate regulation [3]. Forests are one of the primary sinks of carbon. However, these carbon sinks are facing deforestation and forest degradation, which account for 20% of greenhouse gas emissions annually [4]. The Earth has lost 2.3 million km^2 of its forest between the years 2000 and 2012, with an estimated annual global forest loss of 150,000 km^2 area [5,6]. Deforestation can exacerbate the impacts of climate change, worsening the already critical situation if no precautionary measures are taken immediately [7]. The main reason for deforestation and forest degradation is population growth which leads to agriculture expansion, urbanization, and fuel wood collection, mainly in developing countries [8–11]. The United Nation Framework Convention on Climate Change (UNFCCC) parties have formulated a procedure to reduce carbon emissions through the Reducing Emission from Deforestation and Forest Degradation (REDD) mechanism. However, the implementation of this mechanism is still a challenge in the developing world. Examining the importance of forests for a balanced ecosystem, it is recommended that at least 25% of a country's land should be forests to maintain ecological balance [12]. Hence, to control deforestation and forest degradation, it is important to study the changes in forest cover, and its causes on a global, regional, and local scale [13].

The Himalayas are one of the important mountain ranges of Asia, which support the livelihood of 1/6th population of planet Earth [14]. The Himalayas regulate most of Asia's climate and are a fundamental component of the global ecosystem. Deforestation and forest degradation in the Himalayas together with global climate change has effected the local population adversely [14–16]. The Margalla Hills, located in Pakistan, are an important part of the Himalayas; they account for 5% of total forest land in the country [17,18]. The Margalla Hills were declared a "national park", also called MHNP, by the government of Pakistan in 1980, in appraisal of its importance as a crucial component of the country's forest reserve [19,20]. Therefore, it is paramount to study deforestation and forest degradation in the MHNP region.

Methodologically, remote sensing provides continuous monitoring of the Earth's surface, allowing long-term evaluation of forests [21]. Landsat data is mostly used for assessing changes in global forest cover [22]. Various studies employ Landsat for forest cover loss estimation, e.g., [22–26]. Many studies have been carried out for time series assessment of urban area expansion using Landsat data. Supervised classification is mainly used for the analysis [27–29]. Urban area dynamics can be correlated to forest cover change to identify urban expansion as a driver. Forest fires also lead to forest loss and can be a significant driver as well [9,30].

In addition, forest degradation is a slow modification process of land that is difficult to quantify using satellite data [31]. Degradation is a complex and reversible process. It requires repeated measurements of various bio-physical parameters that are spatially and temporally consistent [32,33]. The Vegetation Condition Index (VCI) derived from the Normalized Difference Vegetation Index (NDVI) is calculated from Landsat data as a cumulative measure of deforestation and forest degradation. Unlike NDVI, the VCI can differentiate between the change in vegetation conditions owing to short-term meteorological changes, geographical factors, development activities, and urbanization in the ecological system. Moreover, it is vastly used for drought monitoring [34,35] as well as monitoring changes in vegetation conditions [36]. The VCI is also helpful for identifying the areas where vegetation is under stress [37]. A study conducted in Brazil used the Vegetation Condition Index to monitor the effects of urbanization on vegetation [38].

Moreover, the drivers of forest degradation can be identified by conducting socio-economic surveys. Several scientific studies are based on the socio-economic survey of a forest community to identify direct and indirect drivers of forest degradation [39–41]. Similarly, research conducted in Cambodia evaluated the livelihood of communities relying on forests, and obtained considerable results exploring the main drivers of forest degradation in Phnom Tbeng Forest [39]. Identifying forest loss drivers can help develop conservation strategies, implement policies, and spread awareness, particularly among the local residents [42].

Pakistan has the highest rate of deforestation in South Asia [17]. It has also become the fifth most affected country by climate change [43]. Islamabad, the capital of Pakistan, is adjacent to MHNP. The city is known for its substantial vegetation and plantation cover that is constantly being affected by population growth and urbanization [44]. The strategical decision by the government to declare the Margalla Hills as a "national park" was primarily taken to protect it from urban expansion and the increasing population of the surrounding area. The underlying purpose was to conserve and restore this natural asset by implementing conservation policies. All forms of exploitation and deforestation are thus considered illegal in this area except for specific legalized zones for local communities.

This study is thus an attempt to quantify long-term changes in vegetation condition as an indicator of deforestation and forest degradation and to identify the drivers of change in the Margalla Hills National Park (MHNP). Methodologically, the study employed a mixed method approach in terms of Landsat data, socio-economic survey of the local population, which lives in MHNP area, and structured interviews with stakeholders, i.e., Capital Development Authority (CDA), as a quantitative technique. The findings of this study reflect changes in forest cover after the strategic decision of declaring the Margalla Hills as a "National Park" in 1980. Moreover, the results exhibit whether the conservation measures are successful in the protected area or otherwise.

2. Materials and Methods

2.1. Study Area

Geographically, the Margalla Hills National Park (MHNP) is located at the north end of Islamabad. Figure 1 shows the area of the MHNP in Pakistan's Map. The geographic coordinates of MHNP are 33.0°36″ to 36.0°33″ N latitude and 72.0°50″ to 73.0°26″ E longitude. The Margalla Hills, with 465–1600 m elevation, have mainly limestone rocks. Many streams are found at MHNP, providing fresh water to local wildlife and habitants [45]. The MHNP has a humid subtropical climate [20]. Moreover, the Margalla Hills have a wide range of plant biodiversity [45]. For example, Phulai (*Acacia modesta*), Kao (*Olea ferruginea*), Sanatha (*Dodonaea viscosa*), Granda (*Carissa spinarum*), Ber (*Zizyphus jujuba*), and Lantana (*Lantana camara*) are the main tree species found in the region [46]. The Margalla Hills provide various opportunities for recreational facilities. There are almost 30 villages in the MHNP zone with a population of around seventy thousand [47]. The local community has been living here for several decades and practice a traditional lifestyle. In the case of deforestation and forest degradation, the drivers could be infrastructure-building, urbanization, mining, fuel-wood collection, fires, livestock grazing, and timber logging [48].

The Master Plan for the Margalla Hills National Park was developed in 1979 [49]. According to the ecological baseline study [50], the MHNP has been placed in The World Conservation Union Management Category V (Protected Landscape). Under the Islamabad Wildlife (Protection, Conservation and Management) Ordinance of 1979, most of this area was categorized as a reserved forest before 1960. Later, it was declared a wildlife sanctuary comprising an area of 17,386 ha under the West Pakistan Wildlife Protection Ordinance of 1959. The WWF has been consistently monitoring the status of the MHNP since 1992. In 2009, the WWF carried out the delineation of the MHNP [51]. Despite its status as a National Park, the MHNP has witnessed forest cover loss over the past decade [52]. In 2015, the Islamabad Wildlife Management Board (IWMB) was set up under Section 4 of the Islamabad Wildlife (Protection, Preservation, Conservation and Management Ordinance 1979, Government of Pakistan) [47]. This has, to an extent, helped reduce degradation of the forest cover in the MHNP.

As far as methods and data sources are concerned, Figure 2 explains the general methodology of the study. This research work involves three different types of datasets as mentioned in detail in the following sub-sections. To quantify forest degradation, the VCI has been used while supervised classification has been performed for deforestation assessment. Moreover, a socio-economic survey of the local population was conducted in order to seek information on the causes of deforestation and environmental degradation. In addition, structured interviews of the government officials/policy makers were conducted, which were used in tandem with other methods for quantitative assessment.

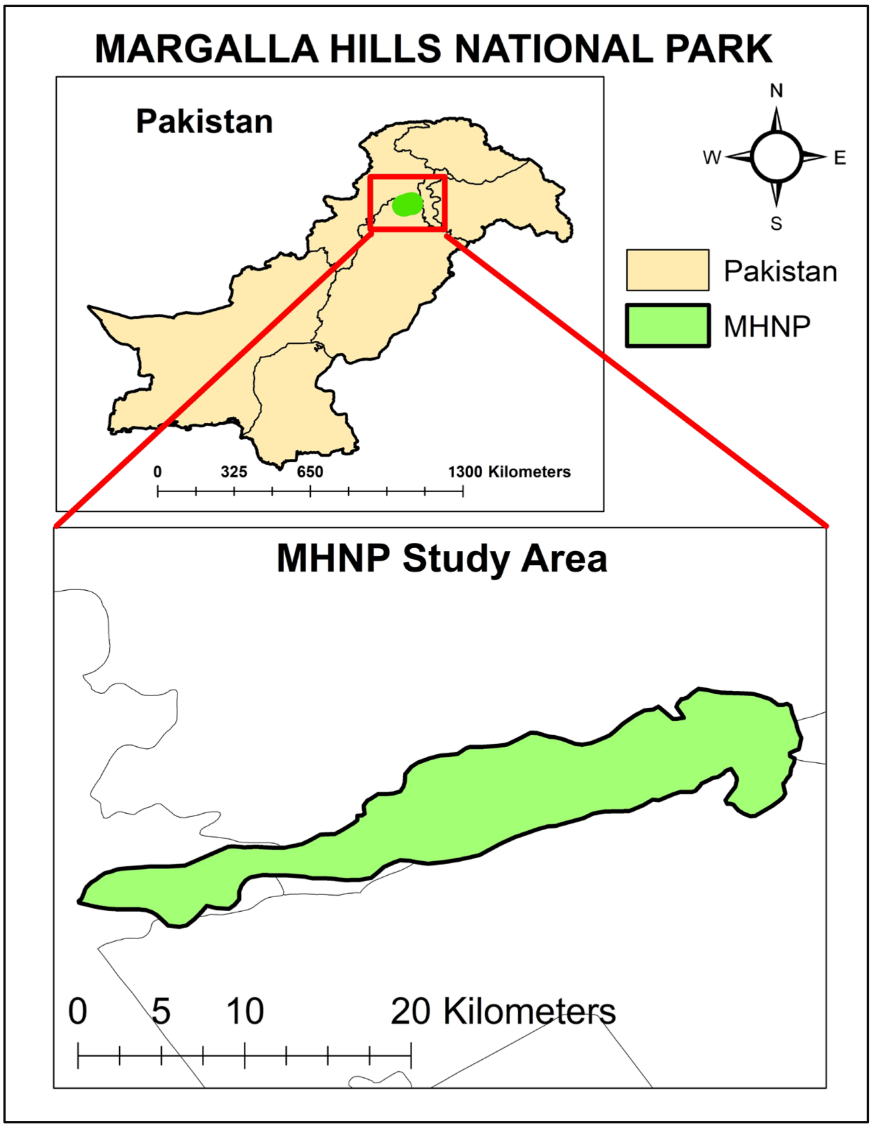

Figure 1. Study area map of the MHNP.

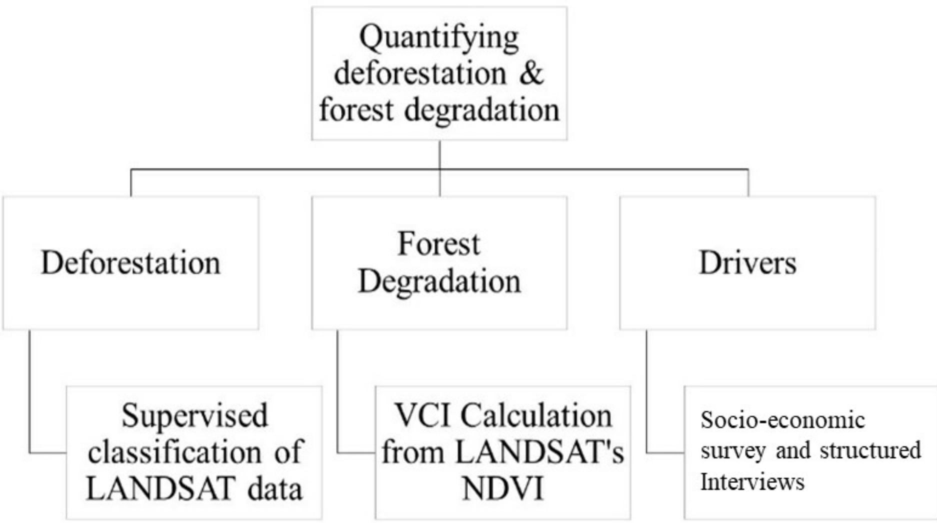

Figure 2. Flow chart of General Methodology.

2.2. Supervised Classification

Supervised classification (maximum likelihood) was performed for the temporal assessment of deforestation and change in urban area from 1988 to 2020 using ArcMap 10.1. A total of 4 images (spectral profiles) were downloaded for the years 1988, 2000, 2010, and 2020 from Landsat 5, 7, and 8. The images were taken from the months of April and May of each year to avoid the seasonal effect of vegetation. A 5 km buffer area around the MHNP boundary was included for classification because it was identified during the survey that people can travel up to 5 km for firewood collection. Thus, the population residing outside the MHNP boundary also affects the forest cover.

The accuracy assessment was performed on the classified image of 2020 only using high-resolution Google Earth imagery as reference data (other years were excluded due to non-availability of high-resolution data for previous years) [27,53]. Stratified random sampling was conducted to collect sample points, and a confusion matrix was created [54].

2.3. Vegetation Condition Index (VCI)

The data used in the study ranged from January 1988 to December 2020 from Landsat 5, 7, and 8 missions. The data was downloaded from the USGS official website. (https://earthexplorer.usgs.gov (accessed on 20 April 2021), Level 2 data: SR product) The images were filtered for the cloud cover (~<10%) before downloading and the Normalized Difference Vegetation Index (NDVI) was calculated for each year (mean) from the surface reflectance of visible (Red) and Near Infrared (NIR) bands [Equation (1)].

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}, \tag{1}$$

The mean NDVIs were calculated for a 5-year interval from 1988 to 2020 that resulted in seven images in total. Using NDVIs (1988–2020), another index, the Vegetation Condition Index (VCI), was computed to represent vegetation condition [Equation (2)] [55,56]. The satellite driven variables (NDVI, VCI) are based on the reflectance by plants because of chlorophyll content and photosynthetic activity [57]. The VCI is better to measure stress in plants than NDVI as it compares the current NDVI to the range of values observed in the same period in previous years [37]. Stress in plants is caused by multiple external factors such as water scarcity, fires, and degradation of leaf content [58]; therefore, the purpose of using the VCI is to have a measure of forest degradation of a particular area over a certain period. The VCI compares the current NDVI to the range of values observed in the same period in previous years, whereas the NDVI is absolute value. The deserted area of the NDVI will always be low. However, the VCI of the deserted area will provide comparison with optimum conditions of the desert. It can inform that a certain year is more or less stressed as compared to a reference year in a particular area.

$$\mathrm{VCI} = \frac{\mathrm{NDVI} - \mathrm{NDVI\ LTMa}}{\mathrm{NDVI\ LTMa} - \mathrm{NDVI\ LTMi}} \times 100, \tag{2}$$

where: NDVI = Normalized Difference Vegetation Index for given time-interval/Pentad; LTMa = long term maximum NDVI, i.e., for whole time-series (1988–2020); LTMi = and long-term minimum NDVI.

The VCI value of each pixel ranges from 0 to 100 (%). It is classified in three categories (Table 1), and the methodology is adopted from drought monitoring classification [59,60]. The area of extreme and moderate degradation was calculated for each interval.

The VCI percentages are calculated and classified in three categories. The values of low VCI percentages (from 0 to 25%) are classified as 'extreme degradation'. The percentages of VCI from 26% to 50% fall in the category of moderate degradation, whereas the percentages above 50% are labelled as 'no degradation-improved vegetation areas'.

Table 1. Classification of VCI (%).

VCI Value	Vegetation Condition
0%–25%	Extreme degradation
26%–50%	Moderate degradation
51%–100%	No degradation–Improved vegetation

2.4. Socio-Economic Survey and Structured Interviews

The methodology for socio-economic survey and analysis was adapted from the following studies [20,41,42,45,52]. The survey among local villagers was carried out to identify direct and indirect drivers of deforestation and forest degradation. For legal considerations, the office of Capital Development Authority (CDA) at the Margalla Hills was consulted before conducting the survey. In addition, for ethical considerations, the village elders were approached, and their permission was sought to conduct the survey in the local population.

The cumulative population of the 30 villages based in the MHNP region is approximately 70,000. The adult population of the said villages, which is adjacent to the federal capital, were selected for the simple random survey which was carried out in March–April 2018.

A questionnaire was developed to know adult perceptions about deforestation and forest degradation activities occurring in the MHNP area. A random-sampling technique was used to carry out the survey. A total of 120 respondents were selected, 20 from each village on the basis of their willingness to participate, and ability to communicate. Out of a total of 120 questionnaires, only 92 questionnaires were returned filled by the respondents—a response rate of 76%. Out of 92 respondents, only 14 were females. All the respondents had received no formal education and relied on daily wage work that is occasionally available.

Along with the socio-economic survey, stakeholders' perceptions were gathered through structured interviews, numbering 20, of CDA officers, forest officers, and other forest officials. Structured interviews were conducted quantitatively through Google Forms to measure percentage of respondents' opinion regarding forest fires, official connivance with the local community for bribery, etc.

For data organization, analysis, and presentation, commonly used software, namely SPSS and Microsoft Excel, were used. The responses from questionnaires were grouped and tabulated, too. In addition, simple statistical functions such as percentages and the mean were applied to generate graphs [39].

Moreover, a regression analysis was also carried out on our results to determine the correlation [61]. XL-STAT software was used for simple linear regression. VCIs, burnt-area due to forest, vegetation area of supervised classification, and other factors were regressed against each other to see the possible correlation between their values. The distance of vegetation cover from urban settlements, roads, and waterways was regressed against vegetation cover trend from the VCI trend analysis.

Additionally, the aforesaid data on forest fires from 1991 to 2017 was obtained from the Capital Development Authority (CDA), Islamabad. The data variables were the frequency of fire events and total burnt area (acre) for each year.

3. Results

3.1. Supervised Classification

Figure 3 shows classified images for visual interpretation in 1988, 2000, 2010, and 2020. A significant change in land use has been observed in the last 32 years. Vegetation has slightly improved while urban areas have shown a notable increase from 1988 to 2020. The forest cover within the MHNP boundary area slightly increased from 136 km^2 in 1988 to 138.2 km^2 in 2020. The total forest cover gain in 32 years is almost 2.2 km^2 (1.6%) in the MHNP boundary. Moreover, urban areas inside the MHNP boundary area increased from 4.5 km^2 in 1988 to 8 km^2 in 2020.

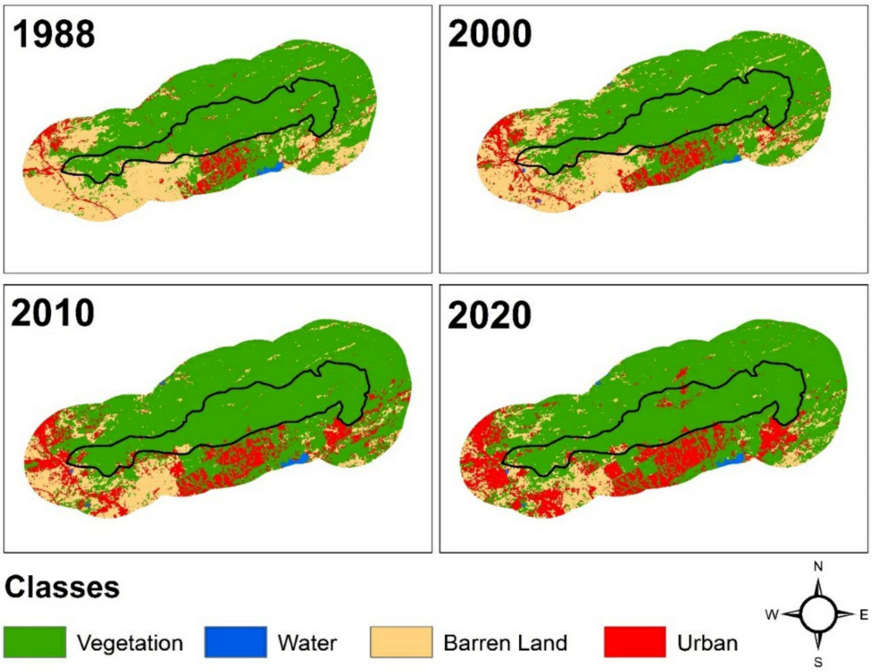

Figure 3. Supervised classification (maximum likelihood) from 1988 to 2020.

The overall study area—MHNP plus 5 km buffer—shows an increase in vegetation from 414 km^2 to 445 km^2 between 1988 and 2020, respectively. The overall urban area—MHNP plus a 5 km buffer—also showed a significant increase during this period, i.e., from 60 km^2 to 118.5 km^2. There were no considerable changes in water bodies, with only an increase of approximately 0.5 km^2. The only part of the land that showed a size reduction was the barren land. Detailed area distribution of each year is shown in Table 2.

Table 2. Area Wise Distribution of Classes from 1988 to 2020 of the complete study areas of the MHNP and Buffer zone (5 km). Area units are in km^2.

	1988	2000	2010	2020
Vegetation	413.81	413.98	446.617	444.844
Urban	59.931	78.3747	105.935	118.627
Water	2.1978	1.4562	2.4192	2.7288
Barren	165.179	147.454	85.9734	75.0969

Table 3 shows the values for user accuracy, kappa coefficient, and overall accuracy. The overall accuracy is 83.6% and the kappa coefficient is 0.78. The urban area's accuracy is 89%. For vegetation, barren land, and water, it is 83%, 85%, and 70%, respectively.

Table 3. Confusion Matrix for accuracy assessment of supervised classification for the year 2020.

	Urban Area Truth	Vegetation/Forest Truth	Barren Land/Soil Truth	Water Truth	Classification Overall	Producer Accuracy Precision
Urban Area	17	0	2	3	22	0.78
Vegetation/Forest	0	15	1	0	16	0.94
Barren Land/Soil	2	1	17	0	20	0.85
Water	0	2	0	7	9	0.78
Truth Overall	19	18	20	10	67	
User Accuracy (Recall)	0.89	0.83	0.85	0.7		
Overall Accuracy	0.84					
Kappa Coefficient	0.78					

3.2. Vegetation Condition Index (VCI)

The classification of the VCI represents the quantification of degradation that has occurred in the MHNP region. The maps of the VCI were identical with scattered and small points of degraded areas (improved and extreme). A histogram is built to show the sum of degradation areas and improved vegetation. The histogram shows that the extreme degradation (0%–25% VCI) has occurred significantly low in the study period. Moderate degradation (25%–50% VCI) has also a decreasing trend till 2020. The sustained or improved vegetation (51%–100%) is the most prominent in the histogram.

Different trails were developed for hiking in the Margalla Hills for public/tourists. These trails have not only provided an opportunity for recreational activities but also easy access for villagers to the capital city. As per the data obtained from Capital Development Authority (CDA), the years when the trails were developed correlate positively with the increase in both severe and moderate degradations of forests as per the VCI. There are a total of six trails (see Table 4), of which Trail 3 was established in 1990. According to Figure 4, the VCI showed a corresponding increase in moderate degradation in the same year. A further greater increase in the forest degradation in the VCI is observed from 2001 to 2015. This was the time during which trails 1, 2, 4, 5, 6, and the Monal restaurant were constructed. Table 4 below shows the respective years of the hiking trails and the development of restaurants in the MHNP by CDA.

Table 4. Year of Establishment of various hiking trails and restaurants in the MHNP, Islamabad.

Trails/Restaurants	Year of Establishment
Trail 1	2003
Trail 2	2003
Trail 3	1990
Trail 4	2009
Trail 5	2009
Trail 6	2007
The Monal Restaurant	2005
La Montana Restaurant	2014

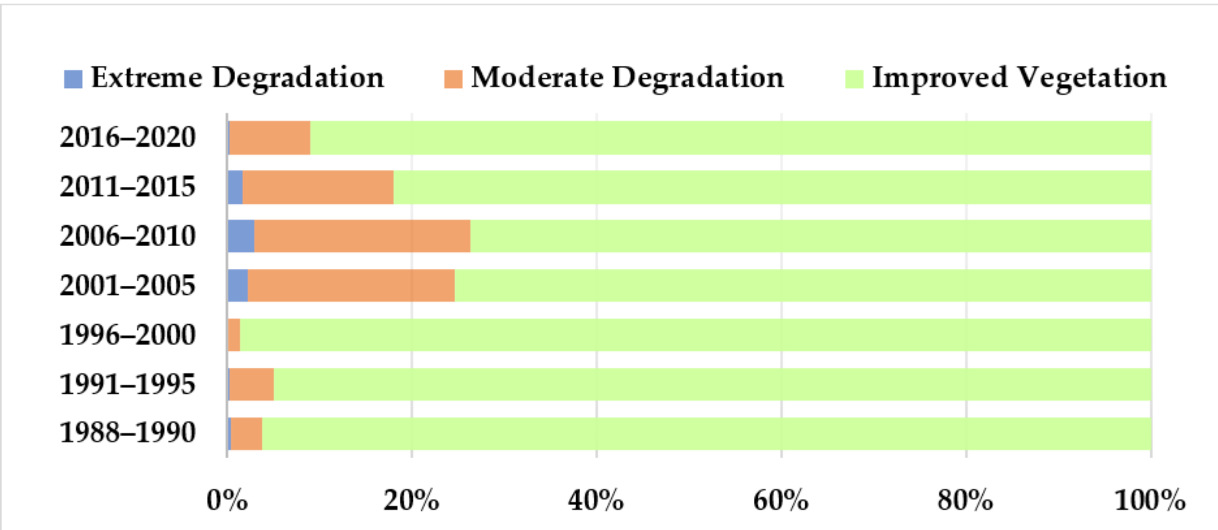

Figure 4. Histogram of the Vegetation Condition Index (VCI) 1988–2020.

3.3. Regression Analysis the Results Show No Correlation between the Variables and Vegetation Trend

Table 5 shows the regression analysis of different variables. The percentages of moderate degradation from the VCI classification were correlated with burnt areas due to forest fires per five years as a driver of forest degradation. No correlation between them was found. Similarly, the forest area from supervised classification for each year is also not correlated with the burnt area in the corresponding year due to forest fires as a driver of deforestation.

Table 5. Regression analysis among various factors.

	VCI—Slope	Moderate Degradation VCI (%)	Forest Area (Supervised Classification)
Distance of vegetation cover from Roads	R^2 = 0.005 (*p*-value 0.001)		
Distance of vegetation cover from settlements	R^2 = 0.001 (*p*-value 0.001)		
Distance of vegetation cover from water ways	R^2 = 0.030 (*p*-value 0.001)		
Forest Fires (Burnt Area)		R^2 = 0.044 (*p*-value 0.001)	R^2 = 0.014 (*p*-value 0.001)

3.4. Survey Data Analysis

Approximately 87% of respondents believed that deforestation and forest degradation is happening in their area, with the highest rate occurring during the winter season. Moreover, 75% of respondents said that deforestation and degradation had affected ecosystem services in their region. A poll showed that 63% respondents considered that deforestation had affected tourism negatively in their area. Only 15% of respondents agreed on quarrying events while 74% reported illegal cutting is being carried out in the MHNP region by the local community and timber mafia.

The villagers were surveyed about the ecosystem services that they avail from the forest. Fuel wood is collected by 100% of respondents whereas 70% of the respondents utilize the forest's water resource. More than 50% said that their cattle use forests for grazing. About 35% of respondents use timber from the forest, and a little more than 20% of respondents extract food from the forest. The results showed that the fuel wood collection is the most important driver due to the non-availability of natural gas in the MHNP villages. In addition, 11% of respondents reported that they sell wood for income generation.

The survey results also showed the most probable causes of fire incidents in the MHNP forests are cigarettes thrown by tourists and residents, causing fire incidents. Respondents also reported that some fires were intentionally started by the local residents in cahoots with the CDA. The former burnt forestry to obtain wood freely while CDA contract employees, who do not have permanent jobs, started fires for easy money while hiding the crime through intentional fires.

Table 6 explains the number of fires, and the total area burnt due to fires in the respective time intervals. From 1991 to 2017, the highest number of fires occurred in 2001–2005, with 1442.8 acres of area affected. Most people consider cigarettes, and tourists barbecuing/grilling responsible for these fires causing extensive damage.

Table 6. Forest Fires Data for MHNP.

	No. of Fires	Total Burnt Area (Acre)
1991–1995	68	188.45
1996–2000	183	1933
2001–2005	220	1442.8
2006–2010	134	851.5
2011–2015	93	364.1
2016–2017	69	143

As reflected in Table 7, the drivers of deforestation and forest degradation identified by the local community were fuel wood collection, lack of energy resources, and fire events. Illegally cutting timber by the timber mafia and local people, urbanization, and encroachment are also the main reasons for degradation and deforestation. Other factors such as land sliding, pest attacks, over grazing, quarrying, and agricultural activities have minimum or almost no role in forest degradation according to the survey results. Infrastructure construction and increasing population has also played a role in deforestation.

Table 7. Community consensus on causes of fire incidents.

Reason of Fire	Consensus of People (%)
Community (Intentional)	28
Tourists (BBQ/grilling)	54
Cigarettes	71
Fire Fighters (Intentional)	50

The survey results have identified forest fires as a dominant driver, but the correlation between degradation and forest fires data have not shown any significant results. The frequency, duration, and scale of the fire events in a year is prominently important for correlation analysis. The yearly averages might not be sufficient to show a correlation with degradation stats.

In addition, the stakeholders' analysis has identified major threats to the MHNP region. According to all twenty officials, deforestation and forest degradation activities are occurring consistently in the MHNP region. Statistically, 95% of interviewees identified urban expansion and infrastructure development as major threats to forest conservation, followed by forest fires and deforestation, whereas the forest management (65%) and CDS officials (50%) recommended environment campaigns and educational programs for the local community, with respect to forest preservation, respectively. Moreover, 50% of officials posited that the local residents were involved in forest degradation activities.

4. Discussion

This study attempted to quantify deforestation and forest degradation in the MHNP, with the aim of identifying its probable causes. The MHNP was exposed to the growing population, urbanization, and expansion of the city. It is the responsibility of the government to preserve the biodiversity of the national park, while some responsibility rests on the public as well, since it is also exposed to exploitation from the surrounding communities [62].

The quantitative analysis showed that forests of the MHNP have been affected by deforestation and degradation overall, but the effect is negligible as the deforestation and degradation is less than 5% of the total area.

Moreover, regression analysis was used to correlate area of deforestation and the VCI with the distance of vegetation cover from urban settlements, roads, and waterways. The R^2 values (with p-value 0.001, and CI 0.95) were not significant ($R^2 < 0.1$), showing no correlation between these variables and the vegetation condition trend.

The VCI (moderate degradation) over a five-year interval was correlated with the burnt area due to forest fires. Similarly, the forest area from supervised classification was also correlated with the burnt area due to forest fires as a driver of deforestation. The R^2 showed no significant correlation among these factors. The reason might be that the forest fire frequency, scale, and duration vary each year drastically, and yearly averages may not be sufficient for such an analysis.

The results have revealed that there Is an increase in forest cover and urbanization, and a decrease in forest degradation and deforestation (data from Landsat 7 and onwards). The forest cover has been degraded if we consider the cumulative results of the past 32 years. The factors may include the development of hiking trails, construction of restaurants, and recreational facilities in the MHNP area since 2000, which increased public entry into the forest region. The results show that not only has the forest's area increased, but the quality of existing forests has also been improved over the years. This is possibly due to the abundance of rainwater (monsoon) and Himalayan run-off at the Margalla Hills, with other factors including sustainable measures by the government taken at the Margalla Hills. The urbanization has occurred on barren land as its area has decreased significantly over the years, i.e., 54% since 1988. The small decrease in vegetation cover from 2010 to 2020, i.e., 0.4%, may indicate the deforestation [26]. It is important to identify if any event of deforestation has happened in the region and what are its likely reasons. To avoid the increased deforestation, a limited deforestation is allowed by the government to the local community in the designated areas for domestic use.

Moreover, the survey data did not reflect any quantitative measure of drivers of deforestation and forest degradation, but it was used to identify the underlying drivers that should be quantified and assessed in future studies that could also be conducted by government institutions [41]. Most of the local community reported the activities of deforestation and forest degradation with negative impacts on ecosystem services in the area. About 74% of respondents reported illegal cutting by the local community and the timber mafia as the main driver of deforestation. The local communities gain multiple benefits from the MHNP including fuel wood, water, livestock grazing, recreational activities, timber, and food. The fuel wood collection is essential and unavoidable due to the non-availability of natural gas/alternative fuels in the MHNP villages. It shows that the local communities majorly depend on the MHNP for their survival, which can result in a continuous impact on the forests [42].

In addition, the survey results identified the most probable causes of fire incidents. The major one is smoking habits of members of the local community and tourists, followed by deliberately lit fires by the members of the community in connivance with the CDA firefighters. The local community want a burnt land to obtain wood freely and CDA firefighters, who do not have permanent jobs, do it for financial incentives earned dubiously. The drivers of deforestation identified by the local community were fuel wood collection, lack of energy resources, fire events, illegal cutting by timber mafia and local people, urbanization, and encroachment. The results also show that no pest attacks and overgrazing occurs in the MHNP, that authenticate the results of forest degradation.

Last but not least, the stakeholders' analysis showed that the infrastructure development and urban expansion are the major threats to the MHNP region. The villagers should be given proper resources to preserve forests. Proper education on the subject should also be provided to the villagers as well as to local tourists.

There is a pressing need for further studies in this domain with an empirical focus in Pakistan, and other developing countries, so that the forests can be conserved. Further studies should be initiated to quantify the drivers of deforestation and degradation. To ensure sustainable measures, the Federal Government of Pakistan should strictly implement biodiversity conservation policies and regulations to conserve the MHNP for posterity.

5. Conclusions

The results of the present study led to the conclusion that the forest cover and urban area have slightly increased in the Margalla Hills National Park region. The spread in urban areas is mostly over the barren land. In the past 32 years, the forest degradation has increased whereas it has decreased if we take 2001 as a base year. The minor deforestation in last 10 years can be due to factors such as increased urbanization, the growing population of local communities, and non-provision of alternatives for the basic needs of the local community, as pointed in the survey. Futuristically, it is vital to protect the biodiversity of the MHNP region through extensive awareness campaigns with the aim to educate the local community as well as local tourists. Moreover, the Federal Government of Pakistan must also make relevant laws, along with modifying the existing environmental regulations, to provide a clear roadmap for policy implementation, with the underlying objective to provide alternative energy sources to local population, curb the timber mafia, and discipline government departments such as the Capital Development Authority. Such measures would, in the long run, help Pakistan realize the climate goals set in the National Climate Change Policy 2021 agenda.

Author Contributions: Supervision and conceptualization, M.F.K. and Z.S.; methodology, E.H., H.A., M.F.K. and Z.S.; writing, H.A., W.R.K., H.J. and E.H.; survey, H.A. and N.u.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by REDD+ Pakistan under the National Internship Program by the REDD-Pakistan organization in collaboration with the World Bank and Government of Pakistan.

Acknowledgments: We would like to thank the REDD-Pakistan's officials for providing their constant support and facilitating us for the research.

Conflicts of Interest: The results from surveys and interviews are all anonymous and might affect a government institute's reputation as some of the data is related to their staff. It is declared that data is anonymous and randomly collected, and not associated with authors personally. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

References

1. Haque, A.E.; Murty, M.N.; Shyamsundar, P. *Environmental Valuation in South Asia*; Cambridge University Press: Cambridge, UK, 2011.
2. Peh, K.S.-H.; Sonké, B.; Séné, O.; Djuikouo, M.-N.K.; Nguembou, C.K.; Taedoumg, H.; Begne, S.K.; Lewis, S.L. Mixed-Forest Species Establishment in a Monodominant Forest in Central Africa: Implications for Tropical Forest Invasibility. *PLoS ONE* **2014**, *9*, e97585. [CrossRef]
3. Jenkins, M.; Schaap, B. Forest ecosystem services. In Proceedings of the 13th Session of United Nations Forum on Forests (UNFF13), New York, NY, USA, 7–11 May 2018.
4. Olander, L.P.; Gibbs, H.K.; Steininger, M.; Swenson, J.J.; Murray, B.C. Reference Scenarios for Deforestation and Forest Degradation in Support of REDD: A Review of Data and Methods. *Environ. Res. Lett.* **2008**, *3*, 025011. [CrossRef]
5. Khalid, N.; Ahmad, S.S.; Erum, S.; Butt, A. Monitoring Forest Cover Change of Margalla Hills Over a Period of Two Decades (1992–2011): A Spatiotemporal Perspective. *J. Ecosys. Ecograph.* **2015**, *6*, 2. [CrossRef]
6. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S.V.; Goetz, S.J.; Loveland, T.R.; et al. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* **2013**, *342*, 850–853. [CrossRef] [PubMed]
7. FAO State of the World's Forests 2012. Available online: http://www.fao.org/docrep/016/i3010e/i3010e00.htm (accessed on 18 May 2018).
8. Allen, J.C.; Barnes, D.F. The Causes of Deforestation in Developing Countries. *Ann. Assoc. Am. Geogr.* **1985**, *75*, 163–184. [CrossRef]
9. Hosonuma, N.; Herold, M.; De Sy, V.; De Fries, R.S.; Brockhaus, M.; Verchot, L.; Angelsen, A.; Romijn, E. An Assessment of Deforestation and Forest Degradation Drivers in Developing Countries. *Environ. Res. Lett.* **2012**, *7*, 044009. [CrossRef]
10. Munawar, S.; Khokhar, M.F.; Atif, S. Reducing Emissions from Deforestation and Forest Degradation Implementation in Northern Pakistan. *Int. Biodeterior. Biodegrad.* **2015**, *102*, 316–323. [CrossRef]
11. Jallat, H.; Khokhar, M.F.; Kudus, K.A.; Nazre, M.; Saqib, N.; Tahir, U.; Khan, W.R. Monitoring Carbon Stock and Land-Use Change in 5000-Year-Old Juniper Forest Stand of Ziarat, Balochistan, through a Synergistic Approach. *Forests* **2021**, *12*, 51. [CrossRef]
12. Khalid, N.; Ullah, S. Tracking Forest Cover Change of Margalla Hills over a Period of Two Decades (1992–2011): A Remote Sensing Perspective. In Proceedings of the 41st COSPAR Scientific Assembly, Istanbul, Turkey, 30 July–7 August 2016; Volume 41.
13. Khuc, Q.V.; Tran, B.Q.; Meyfroidt, P.; Paschke, M.W. Drivers of Deforestation and Forest Degradation in Vietnam: An Exploratory Analysis at the National Level. *For. Policy Econ.* **2018**, *90*, 128–141. [CrossRef]
14. Singh, S.P.; Thadani, R. Complexities and Controversies in Himalayan Research: A Call for Collaboration and Rigor for Better Data. *Mt. Res. Dev.* **2015**, *35*, 401–409. [CrossRef]
15. Romshoo, S.A.; Rashid, I. Assessing the Impacts of Changing Land Cover and Climate on Hokersar Wetland in Indian Himalayas. *Arab. J. Geosci.* **2014**, *7*, 143–160. [CrossRef]
16. Singh, S.P.; Gumber, S. Climate Change in Himalayas: Research Findings and Complexities. *Int. J. Plant Environ.* **2018**, *4*, 1–13. [CrossRef]
17. Khalid, N.; Ullah, S.; Ahmad, S.S.; Ali, A.; Chishtie, F. A Remotely Sensed Tracking of Forest Cover and Associated Temperature Change in Margalla Hills. *Int. J. Digit. Earth* **2019**, *12*, 1133–1150. [CrossRef]
18. UNDP Forests and Bio Diversity–Information/Data Report. Available online: http://www.pk.undp.org/content/pakistan/en/home/library/environment_energy/publication_2.html (accessed on 18 May 2018).

19. Ahmad, S.S. Ordination and Classification of Herbaceous Vegetation in Margalla Hills National Park Islamabad Pakistan. *Biol. Divers. Conserv.* **2009**, *2*, 38–44.
20. Ali, S.; Khan, S.M.; Siddiq, Z.; Ahmad, Z.; Ahmad, K.S.; Abdullah, A.; Hashem, A.; Al-Arjani, A.-B.F.; Abd_Allah, E.F. Carbon sequestration potential of reserve forests present in the protected Margalla Hills National Park. *J. King Saud Univ. Sci.* **2022**, *34*, 101978. [CrossRef]
21. Lambin, E.F.; Geist, H.J.; Lepers, E. Dynamics of Land-Use and Land-Cover Change in Tropical Regions. *Annu. Rev. Environ. Resour.* **2003**, *28*, 205–241. [CrossRef]
22. Kim, D.-H.; Sexton, J.O.; Noojipady, P.; Huang, C.; Anand, A.; Channan, S.; Feng, M.; Townshend, J.R. Global, Landsat-Based Forest-Cover Change from 1990 to 2000. *Remote Sens. Environ.* **2014**, *155*, 178–193. [CrossRef]
23. Margono, B.A.; Potapov, P.V.; Turubanova, S.; Stolle, F.; Hansen, M.C. Primary Forest Cover Loss in Indonesia over 2000–2012. *Nat. Clim. Change* **2014**, *4*, 730. [CrossRef]
24. Potapov, P.V.; Turubanova, S.A.; Hansen, M.C.; Adusei, B.; Broich, M.; Altstatt, A.; Mane, L.; Justice, C.O. Quantifying Forest Cover Loss in Democratic Republic of the Congo, 2000–2010, with Landsat ETM+ Data. *Remote Sens. Environ.* **2012**, *122*, 106–116. [CrossRef]
25. Potapov, P.V.; Turubanova, S.A.; Tyukavina, A.; Krylov, A.M.; McCarty, J.L.; Radeloff, V.C.; Hansen, M.C. Eastern Europe's Forest Cover Dynamics from 1985 to 2012 Quantified from the Full Landsat Archive. *Remote Sens. Environ.* **2015**, *159*, 28–43. [CrossRef]
26. Zeb, A. Spatial and Temporal Trends of Forest Cover as a Response to Policy Interventions in the District Chitral, Pakistan. *Appl. Geogr.* **2019**, *102*, 39–46. [CrossRef]
27. Xu, H. Extraction of Urban Built-up Land Features from Landsat Imagery Using a Thematicoriented Index Combination Technique. *Photogramm. Eng. Remote Sens.* **2007**, *73*, 1381–1391. [CrossRef]
28. Mwakapuja, F.; Liwa, E.; Kashaigili, J. Usage of Indices for Extraction of Built-up Areas and Vegetation Features from Landsat TM Image: A Case of Dar Es Salaam and Kisarawe Peri-Urban Areas, Tanzania. *Int. J. Agric. For.* **2013**, *3*, 273–283.
29. Li, X.; Gong, P.; Liang, L. A 30-Year (1984–2013) Record of Annual Urban Dynamics of Beijing City Derived from Landsat Data. *Remote Sens. Environ.* **2015**, *166*, 78–90. [CrossRef]
30. van der Werf, G.R.; Randerson, J.T.; Giglio, L.; Collatz, G.J.; Mu, M.; Kasibhatla, P.S.; Morton, D.C.; DeFries, R.S.; Jin, Y.; Leeuwen, T.T. van Global Fire Emissions and the Contribution of Deforestation, Savanna, Forest, Agricultural, and Peat Fires (1997–2009). *Atmos. Chem. Phys.* **2010**, *10*, 11707–11735. [CrossRef]
31. Houghton, R.A. Carbon Emissions and the Drivers of Deforestation and Forest Degradation in the Tropics. *Curr. Opin. Environ. Sustain.* **2012**, *4*, 597–603. [CrossRef]
32. Lambin, E.F. Monitoring Forest Degradation in Tropical Regions by Remote Sensing: Some Methodological Issues. *Glob. Ecol. Biogeogr.* **1999**, *8*, 191–198. [CrossRef]
33. Miettinen, J.; Stibig, H.-J.; Achard, F. Remote Sensing of Forest Degradation in Southeast Asia—Aiming for a Regional View through 5–30 m Satellite Data. *Glob. Ecol. Conserv.* **2014**, *2*, 24–36. [CrossRef]
34. Kogan, F.N. Remote Sensing of Weather Impacts on Vegetation in Non-Homogeneous Areas. *Int. J. Remote Sens.* **1990**, *11*, 1405–1419. [CrossRef]
35. Vilanova, R.S.; Delgado, R.C.; da Silva Abel, E.L.; Teodoro, P.E.; Silva Junior, C.A.; Wanderley, H.S.; Capristo-Silva, G.F. Past and Future Assessment of Vegetation Activity for the State of Amazonas-Brazil. *Remote Sens. Appl. Soc. Environ.* **2020**, *17*, 100278. [CrossRef]
36. Amalo, L.F.; Hidayat, R. Comparison between Remote-Sensing-Based Drought Indices in East Java. In Proceedings of the IOP Conference Series: Earth and Environmental Science, Bogor, Indonesia, 25–26 October 2016; IOP Publishing: Bristol, UK; Volume 54, p. 012009.
37. Liang, L.; Sun, Q.; Luo, X.; Wang, J.; Zhang, L.; Deng, M.; Di, L.; Liu, Z. Long-Term Spatial and Temporal Variations of Vegetative Drought Based on Vegetation Condition Index in China. *Ecosphere* **2017**, *8*, e01919. [CrossRef]
38. Brandalise, M.; Prandel, J.; Quadros, F.; Rovani, I.; Malysz, M.; Decian, V. Influence of Urbanization on the Dynamics of the Urban Vegetation Coverage Index (VCI) in Erechim (RS). *Floresta E Ambiente* **2019**, *26*, 2. [CrossRef]
39. Chan, S.; Sasaki, N. Assessment of Drivers of Deforestation and Forest Degradation in Phnom Tbeng Forest Based on Socio-Economic Surveys. *J. Environ. Prot.* **2014**, *5*, 1641. [CrossRef]
40. Kessy, J.F.; Nsokko, E.; Kaswamila, A.; Kimaro, F. Analysis of Drivers and Agents of Deforestation and Forest Degradation in Masito Forests, Kigoma, Tanzania. *Int. J. Asian Soc. Sci.* **2016**, *6*, 93–107. [CrossRef]
41. Zeb, A.; Armstrong, G.W.; Hamann, A. Forest Conversion by the Indigenous Kalasha of Pakistan: A Household Level Analysis of Socioeconomic Drivers. *Glob. Environ. Change* **2019**, *59*, 102004. [CrossRef]
42. Zeb, A.; Hamann, A.; Armstrong, G.W.; Acuna-Castellanos, D. Identifying Local Actors of Deforestation and Forest Degradation in the Kalasha Valleys of Pakistan. *For. Policy Econ.* **2019**, *104*, 56–64. [CrossRef]
43. Kreft, S.; Eckstein, D.; Melchior, I. Who Suffers Most From Extreme Weather Events? Weather-Related Loss Events in 2015 and 1996 to 2015. In *Global Climate Risk Index*; Germanwatch e.V.: Bonn, Germany, 2016.
44. Shah, A.; Ali, K.; Nizami, S.M. Spatio-temporal analysis of urban sprawl in Islamabad, Pakistan during 1979–2019, using remote sensing. *GeoJournal* **2021**, *87*, 2935–2948. [CrossRef]
45. AdYasmin, N.; Khokhar, M.F.; Tanveer, S.; Saqib, Z.; Khan, W.R. Dynamical Assessment of Vegetation Trends over Margalla Hills National Park by Using MODIS Vegetation Indices. *Pak. J. Agric. Sci.* **2016**, *53*, 777–786.

46. WWF. *Boundary Dilineation of Margalla Hills National Park*; GIS Laboratory, WWF Pakistan: Islamabad, Pakistan, 2009.
47. *Yearbook 2018–2019*; Ministry of Climate Change, Government of Pakistan: Islamabad Pakistan, 2019.
48. UNEP Course: REDD+ Academy e-Course. Available online: https://unccelearn.org/course/view.php?id=16# (accessed on 18 May 2018).
49. Masud, R.M. *Master Plan for the Margalla Hills National Park, Islamabad Pakistan, 1979–1984*; Ministry of Food, Agriculture and CooperativesPakistan, National Council for Conservation of Wildlife (NCCW): Islamabad, Pakistan, 1979.
50. Himalayan Wildlife Foundation. *Margalla Hills National Park Ecological Baseline*; Himalayan Wildlife Foundation: Islamabad, Pakistan, 2007.
51. Margalla Hills National Park. Pakistan. *HWF Himal. Wildl. Found.* 2021. Available online: http://hwf.org.pk/ (accessed on 3 July 2021).
52. Khalid, F.; Taj, M.B.; Jamil, A.; Raheel, A.; Sharif, M.; Kamal, H.; Afzal, T.; Khan, T.; Iqbal, M.J.; Ashiq, M. Micro-Level Study of Deforestation in the Capital Terrotory of Pakistan. *Pak. J. Sci. Ind. Res. Ser. Phys. Sci.* **2021**, *64*, 222–232. [CrossRef]
53. Li, X.; Zhou, Y.; Zhu, Z.; Liang, L.; Yu, B.; Cao, W. Mapping Annual Urban Dynamics (1985–2015) Using Time Series of Landsat Data. *Remote Sens. Environ.* **2018**, *216*, 674–683. [CrossRef]
54. Congalton, R.G. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sens. Environ.* **1991**, *37*, 35–46. [CrossRef]
55. Roy, D.P.; Kovalskyy, V.; Zhang, H.K.; Vermote, E.F.; Yan, L.; Kumar, S.S.; Egorov, A. Characterization of Landsat-7 to Landsat-8 Reflective Wavelength and Normalized Difference Vegetation Index Continuity. *Remote Sens. Environ.* **2016**, *185*, 57–70. [CrossRef]
56. Kogan, F.; Stark, R.; Gitelson, A.; Jargalsaikhan, L.; Dugrajav, C.; Tsooj, S. Derivation of Pasture Biomass in Mongolia from AVHRR-Based Vegetation Health Indices. *Int. J. Remote Sens.* **2004**, *25*, 2889–2896. [CrossRef]
57. Tucker, C.J. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* **1979**, *8*, 127–150. [CrossRef]
58. Lichtenthaler, H.K. Vegetation Stress: An Introduction to the Stress Concept in Plants. *J. Plant Physiol.* **1996**, *148*, 4–14. [CrossRef]
59. Bhuiyan, C.; Singh, R.P.; Kogan, F.N. Monitoring Drought Dynamics in the Aravalli Region (India) Using Different Indices Based on Ground and Remote Sensing Data. *Int. J. Appl. Earth Obs. Geoinf.* **2006**, *8*, 289–302. [CrossRef]
60. Yagci, A.L.; Di, L.; Deng, M. The Effect of Land-Cover Change on Vegetation Greenness-Based Satellite Agricultural Drought Indicators: A Case Study in the Southwest Climate Division of Indiana, USA. *Int. J. Remote Sens.* **2013**, *34*, 6947–6968. [CrossRef]
61. Eckert, S.; Hüsler, F.; Liniger, H.; Hodel, E. Trend Analysis of MODIS NDVI Time Series for Detecting Land Degradation and Regeneration in Mongolia. *J. Arid Environ.* **2015**, *113*, 16–28. [CrossRef]
62. Khalid, F.; Taj, M.B.; Jamil, A.; Kamal, H.; Afzal, T.; Iqbal, M.J.; Khan, T.; Ashiq, M.; Raheel, A.; Sharif, M. Deforestation Dynamics in Pakistan: A Critical Review: Deforestation Dynamics. *Proc. Pak. Acad. Sci. B Life Environ. Sci.* **2020**, *57*, 27–34.