



Technical Note

# Mapping Deforestation and Forest Degradation Patterns in Western Himalaya, Pakistan

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Abstract: The Himalayan mountain forest ecosystem has been degrading since the British ruled the area in the 1850s. Local understanding of the patterns and processes of degradation is desperately required to devise management strategies to halt this degradation and provide long-term sustainability. This work comprises a satellite image based study in combination with national expert validation to generate sub-district level statistics for forest cover over the Western Himalaya, Pakistan, which accounts for approximately 67% of the total forest cover of the country. The time series of forest cover maps (1990, 2000, 2010) reveal extensive deforestation in the area. Indeed, approximately 170,684 ha of forest has been lost, which amounts to 0.38% per year clear cut or severely degraded during the last 20 years. A significant increase in the rate of deforestation is observed in the second half of the study period, where much of the loss occurs at the western borders along with Afghanistan. The current study is the first systematic and comprehensive effort to map changes to forest cover in Northern Pakistan. Deforestation hotspots identified at the sub-district level provide important insight into deforestation patterns, which may facilitate the development of appropriate forest conservation and management strategies in the country.

Keywords: environmental degradation; forest monitoring; land degradation

## 1. Introduction

Himalayan mountain ecosystems are under severe stress because of population pressure [1,2] amplified by climate change [3]. For this reason, habitat fragmentation and degradation are clearly evident [4–6]. Massive forest destruction began in this region during the early British Government rule (1850s), when forest wood was consumed for infrastructure development and commercial use [7,8]. According to reference [9], three quarters of the Western Himalayan forest coverage has been lost since the last century, while reference [10] observed that losses in the western region remained higher (23%) than the eastern region (7%) of the Himalaya during the last three decades.

Most forest studies within this region have concentrated on the Eastern Himalayas in Nepal and India, with the results extrapolated to the entire Himalayan region [7]. Until recently, adequate attention has not been given to understand the cryosphere (*i.e.*, glaciers, snow and permafrost) dynamics in the Western Himalayas, where evidence suggests anomalous results relative to the Eastern

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Himalayas [11]. Still, a comprehensive understanding of the ecological conditions (e.g., rangelands, forest, and biodiversity) remains incomplete for this region of the Himalayas.

In Pakistan, the current forest cover extent and deforestation rates are contentious issues among stakeholders. According to the first comprehensive remote sensing based on a national land cover assessment under the Forestry Sector Master Plan (FSMP), the forest area totals 3.59 million ha, which is 4.1% of the total land area of Pakistan [12]. Out of this 3.59 million ha, approximately 67% of the forest area exists in the province Khyber Pakhtunkhwa (1.49 million ha), the administrative region Gilgit-Baltistan (0.66 million ha) and the state of Azad Jammu and Kashmir (0.26 million ha) in the Western Himalaya. Taking the FSMP study as the baseline, a national forest and range resource study observed that annual deforestation in natural forests was 27,000 ha during 1990-2000, giving an annual decline of 0.7%. The Global Forest Resource Assessment reported forest cover to be 2.5 million ha, 2.1 million ha and 1.7 million ha for the years 1990, 2000 and 2010, respectively; hence, the forest cover rate of change during the first decade was -1.6% per annum and -2.0% per annum during the second decade [13]. Similarly, the World Bank reports Pakistan's total forest cover to be 2.2% of its total land area [14]. This situation is similar to several global assessments that refer to various figures on the extent of global forest coverage, which can also be partly attributed to a lack of a clear definition of "forest land" [15]. Few countries have reliable data from comparable assessments over time [13], and this lack of data is a sizable obstacle for efficient forest management policies in these countries. This review highlights the lack of systematic assessments and large area estimates of changes to forest cover in Pakistan.

Because the United States Geological Survey (USGS) is continuing to acquire global satellite images through Landsat 8 [16] and has made the archived images publicly available [17], there is the possibility to monitor forest changes both retrospectively and prospectively. In addition to being timely and cost effective [18], satellite based monitoring enables a transparent and reliable [19] means to monitor forest cover conditions. Although errors in the interpretation of spectral response and human bias exist [20,21], remote sensing remains to play key role in identifying and estimating deforested and reforested areas [22,23]. In the Himalayas, the application of remote sensing was introduced in the mid-1980s [24] to identify and analyze the Land Use Land Cover (LULC) pattern [25–27]. Through the analysis of the spatial and temporal patterns of deforestation and the identification of key variables related to deforestation, efforts are being made to identify the driving forces behind changes to forest cover [28–32].

The objective of this study is to produce reliable large-scale datasets on the extent of forest cover and its changing trends by way of comprehensive mapping of forest cover in the mountain region of Western Himalaya, Pakistan.

# 2. Materials and Methods

# 2.1. Study Area

Geographically, the study area is in the extreme north of Pakistan, lying between  $31^{\circ}30'-37^{\circ}00'N$  and  $69^{\circ}00'-77^{\circ}30'E$ . Three different authorities administer the region, including the Khyber Pakhtunkhwa (KP) province, the administrative unit of Gilgit-Baltistan (GB) and the state of Azad Jammu and Kashmir (AJK). The total area covered in the study is approximately 18,260,000 ha (GB = 6,900,000; KP = 10,170,000; AJK = 1,190,000), which is 23% of the total land area of Pakistan and contains approximately 67% of the total forest cover of Pakistan.

The vegetation in the Himalayas, as in any mountainous region, is essentially determined by the topography, climate, geology, rocks and soil. The Western Himalayas is a zone of lower monsoon rainfall in the summer and heavy snow fall in the winter. The classification of Himalayan vegetation into broad categories has been characterized by reference [33] and later refined for Pakistan [34]. A wide variety of forest types are found in Western Himalayas ranging from tropical forest to alpine scrub, which can be classified into seven major classes (Figure 1) [34].

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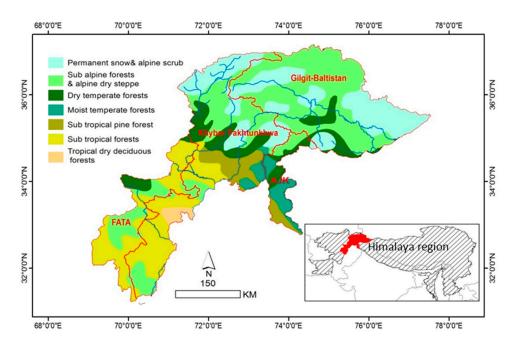


Figure 1. Study area and forest types of the region.

Alpine Scrub: This type of forest begins immediately above the tree limit at 3600 m and extends until 4900 m. This zone comprises stunted woods alternating with meadows. The scrub consists of *Junipreus squamata*, *Junipreus recurva*, etc.

Sub Alpine Forests: These forests lay immediately above the temperate zone forest at the tree line extending from 3000–3800 m.

Dry Temperate Forests: The principal components of this forest type are *Cedrus deodara* and *Pinus wallichiana*, which occupy belts ranging from 1550 m to 3300 m.

Moist Temperate Forests: This forest type comprises evergreen oaks and conifers that cover the temperate zone of Western Himalaya between an altitude of 1500–3000 m. The dominant species in this region are *Cedrus deodara*, *Picea smythiana* and the oak species *Quercus incana* and *Quercus dilatata*.

Sub-Tropical Coniferous Forests: Formations of *Pinus roxburghi* cover the entire outer range between altitudes of 800–1800 m. In its lower elevation zones, this region is mixed with species such as *Shorea robusta*, and on its upper altitude range it is associated with species such as *Quercus incana*.

Sub Tropical (broad leaved) Forests: Elevation ranges between 350–1000 m, mean annual temperatures of 21  $^{\circ}$ C–27  $^{\circ}$ C and average humidity of 50%–60%. These are forests of low or moderate height and mostly consist of deciduous tree species.

Tropical Dry Deciduous Forests: These occur along foothills and are found to an elevation of 1300 m with *Shorea robusta* as the dominant species.

## 2.2. Datasets

To interpret the land cover, Level 1 terrain corrected (L1T) temporal Landsat data, which is available from the USGS EROS [35], for 1990, 2000 and 2010 ( $\pm 2$  years) were used. For the acquisition of optical satellite data in northern Pakistan, the months of August to October are considered to be the most suitable because of the least amount of cloud and snow cover during this period. The entire archive was examined thoroughly to locate the images captured during September and October (Table S1, Supplementary Material). Bearing in mind the extensive temporal record and relatively consistent spatial and radiometric characteristics, the Landsat satellite data offers a reliable source of appropriate resolution data that is critical for the quantification of land change over reasonably long time periods [36]. The data for the administrative boundaries at the sub-district level was accessed from the data portal in reference [37].

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## 2.3. Data Pre-Processing

The use of multi-temporal satellite data for large area mapping poses a number of challenges, including geometric correction errors, noise arising from atmospheric effects and changing illumination errors [38]. For these reasons, pre-processing is necessary to remove or minimize such errors. The pre-processing steps used in this study included Top of Atmosphere (TOA) reflectance conversion, Bi-directional reflectance distribution function BRDF/View angle normalization, and cloud masking. Each image was normalized for solar irradiance by converting the digital number values to TOA reflectance. This conversion algorithm is "physically based, automated, and does not introduce significant errors to the data" [39]. Corrections for BRDF effects were performed to the TOA image by employing a per scene BRDF adjustment. Reference [40] showed that per scene BRDF adjustments improve radiometric response and land cover characterizations. A total of 57 (19  $\times$  3) satellite images were processed individually. Subsequently, TOA reflectance was converted into ground reflectance through an atmospheric correction process. Second Simulation of the Satellite Signal in the Solar Spectrum (6S) is an advanced radiative transfer code that is designed to simulate the solar radiation reflectance by a coupled atmosphere-surface system for a wide range of atmospheric, spectral and geometric conditions [41]. The code calculates the atmospheric correction coefficients xa, xb and xc for each band separately based on the input data, providing an indication of the most likely atmospheric conditions during image acquisition. These atmospheric correction coefficients are applied to the Top of Atmosphere (TOA) radiance (Lsat  $\lambda$ ) to obtain SR values for each band. Using the 6S model, the SR ( $\rho$ ) free from atmospheric effects was calculated using Equation (1).

$$\rho = \frac{Y}{1.0 + (xc * Y)}\tag{1}$$

where  $Y=(xa\times L_{sat\lambda})-xb$ . xa is the inverse of transmittance, xb is the scattering term of the atmosphere and xc is the reflectance of the atmosphere for isotropic light.

Information on the solar zenith angle, solar azimuth angle, sensor zenith angle, sensor azimuth angle and image acquisition date and time were extracted from the image metadata file, whereas the water vapour and aerosol optical depth values were retrieved from MODIS Terra Daily Level-3 ( $1^{\circ} \times 1^{\circ}$ ) global atmospheric product (MOD08\_D3.051) from [42]. Columnar ozone data were retrieved from the OMI Daily Level-3 ( $0.25^{\circ} \times 0.25^{\circ}$ ) global gridded product from [42]. Additionally, the 6S model accounts for adjacency effects based on the view and azimuth angles of the sensor [43].

The topography of mountainous areas causes reflectance issues that must be corrected for the subsequent analysis of the associated satellite data. In this study, the C-correction [44,45] method was applied to compensate for differences in solar illumination induced by the topography using SAGA GIS [46].

# 2.4. Image Classification

The foremost step is the identification of classes that are to be mapped. Conventionally, the system would contain classes that are exhaustive and mutually exclusive; in fuzzy systems, this requirement can be relaxed, allowing intergradations of classes and mixed communities [15]. To keep the current land cover classes comparable with previous efforts, earlier studies were reviewed, including the Forestry Sector Master Plan [12], the National Forest and Range Resource Assessment [47], the Provincial Forest Resource Inventory (PFRI) of North West Frontier Province—Pakistan [48] and the Ecological Mapping and Monitoring for the Mountain Areas Conservancy Project [49]. Fourteen land cover classes were identified (Table 1). A Minimum Mapping Unit (MMU) of ~1 ha (3 × 3 pixels) is chosen to quantify the forest cover.

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Table 1. Land cover classes used in the study.

Name	Description
Dense Coniferous Forest (DCF)	Densely distributed evergreen needle-leaved forest with canopy cover greater than 60%, which mainly includes moist and dry temperate Himalayan forest, sub alpine forest and sub tropical pine forest.
Sparse Coniferous Forest (SCF)	Sparsely distributed evergreen needle-leaved forest with canopy cover less than 60% mixed with scrubs, bare areas and grasses/shrubs.
Dense Mix Forest (DMF)	Includes mixed forest of evergreen needle-leaved and broadleaved trees and scrub forest with density more than 60%.
Sparse Mix Forest (SMF)	Includes mix forest of evergreen needle-leaved and broadleaved trees and scrub forest with density less than 60% mixed with scrubs, bare areas and grasses/shrubs.
Dense Broadleaved Forest (DBF)	Densely distributed broadleaved and scrub forest with canopy cover greater than 60%.
Sparse Broadleaved Forest (SBF)	Sparsely distributed broadleaved and scrub forest with canopy cover less than 60% mixed with scrubs, bare areas and grasses/shrubs.
Grasses/Shrubs (GS)	Consists of grasses and shrubs that are difficult to differentiate because of spatial resolution limitations, and shrubs in the upper mountainous region of Pakistan are mainly dwarf shrubs that are found mixed with grasses.
Alpine Grasses (AG)	Alpine pasture above 4000 m elevation fall under this class.
Peatlands (P)	Includes a naturally accumulated layer of peat mixed with standing water mostly found at high elevation.
Agriculture (Cropped) (AC)	Depending on the season, cultivated or agriculture fields are classified into two categories: mature and grown fields are cropped and harvested fields are fallow.
Agriculture (Fallow) (AF)	Harvested agriculture fields.
Bare Soil/Rocks (BSR)	Non-vegetation areas, which include river sand, mud, barren land and rocks.
Snow/Glaciers/Ice (SGI)	Includes both perennial and non-perennial snow and ice.
Water bodies (W)	Includes both small and large water tributaries that can be classified and standing water bodies ( <i>i.e.</i> , lakes and dams).

There are a plethora of methods that can be used to map forest cover using satellite imagery. However, forest cover maps have been derived from methods that are relatively effort-intense [45,47]. This study used a semi-automated (*i.e.*, computer-assisted) classification technique, which requires less time and is less interpreter-dependent than techniques based on visual interpretations. Performing a semi-automated classification, such as supervised classification, is desirable to provide reliable data over time to monitor the future state of forests [50,51]. The training areas (or spectral signatures collected during the training phase) can easily be used and refined (if new information is available) in future exercises of similar nature [52].

Landsat satellite images taken in 2010 are foremost for the classification process. Training sites were identified and marked on the satellite data by polygons, which represent homogenous areas for each land-cover type. More than 200 training samples containing at least 10–15 pure training samples for each land-cover type were compiled. The source of these training areas was a combination of GPS based ground observation data compiled from previous land cover reports and visualization of high-resolution images from Google Earth. Based on the identified representative training areas, we performed signature evaluation through exploratory histogram analysis, computing signature separability using divergence between the distance between signatures and the contingency matrix to provide a basis for deciding whether to retain, merge, reshape, or take new training sites. Initially, mean values of training site samples were displayed with rectangular or elliptic boundaries on scatter

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plots of the spectral band combinations. The distance image and output thematic raster layer produced by Maximum Likelihood Classifier were used to identify those most likely to be misclassified. The histogram tails were cut-off interactively. Once the collected signatures were satisfactorily compared, multiple signatures were merged into one signature for a given land cover category and used for the classification. On the basis of the training areas and the spectral signature, the satellite image for the entire area resulted in a land cover map with 14 classes. Similarly, satellite images from years 2000 and 1990 were also processed by a similar approach for the classification of historic datasets. Individual pixels were re-sampled by applying a  $3 \times 3$  majority filter to remove noise from the resultant land cover map; hence, we obtained a Minimum Mapping Unit (MMU) of ~1 ha ( $3 \times 3$  pixels) for the first draft of the land cover map.

# 2.5. Forest Cover and Change Statistics

The land cover was primarily classified into 14 classes (Table 1), including six forest cover classes (*i.e.*, dense coniferous forest, sparse coniferous forest, dense mixed forest, sparse mixed forest, sparse broadleaved forest) and eight non-forest cover classes (*i.e.*, grassland/shrubs, alpine grassland, agriculture, bare soil/rocks, snow/glaciers/ice, water bodies). The transition from forest to non-forest was considered to be deforestation and dense forest to sparse forest was considered to be degradation. We employed FAO's definition of deforestation which does not distinguish natural loss of forest from that caused by human action [53,54].

The change in forest cover classes was quantified using the output layers of land cover for three different years and cross tabulation between layers using the spatial analysis tool in ArcGIS. Changes other than forest are beyond the scope of the present work and were not extensively investigated. Thus, the accuracy of these classes is limited.

## 2.6. Interpretation Review by National Experts

Digital classification can be subject to misinterpretation caused by environmental conditions at the time of image acquisition (e.g., clouds, fog, etc.), variations in local forest types or limitations in computational algorithms. To address these limitations, professionals with backgrounds in remote sensing and strong ecological knowledge of the local area were invited to review the digital classification. To this end, experts from the WWF—Pakistan, the Karakorum International University and the National Agriculture Research Center (NARC) conducted a thorough review of 50 sub-districts during one month period.

Based on the observations on classification errors by these experts, improvements in the land cover were performed. A set of factors based on the threshold and conditionality of elevation, slope, aspect and spectral image indices of wetness index, shadow index, greenness index, snow index, among others (S1, Supplementary material), was compiled to improve the description of land cover. All the statistics were recomputed with these improved land cover datasets.

## 2.7. Accuracy Assessment

The accuracy of the land cover maps developed from Landsat satellite images was assessed by comparing the land cover results with Google Earth based on very high resolution satellite (VHRS) images (VHRI). A systematic quarter degree (25 km) grid was developed and visualized on high-resolution satellite images of Google Earth. A total of 287 centre points of the grid are within the study area. While examining the observations possible via Google Earth, a simplified land cover with two classes of forest (*i.e.*, Dense Forest and Sparse Forest) and other general classes of land cover was compared at each grid centroid for the purpose of validation. Based these observations, a systematic accuracy assessment was performed for the 2010 land cover map, as most of the Google Earth images were taken from 2007 to 2010. In addition, effort was made to validate deforestation and degradation patches by using time series Google Earth images available during 2000–2010.

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#### 3. Results

#### 3.1. General Land Cover Distribution

Three land cover maps with 14 land cover classes were prepared for each of the three provinces. The area cover distribution and changes during two decades are given in Tables 2 and 3 (Tables S2–S7, Supplementary material). According to a recent land cover map, there is, in general, 12% of forest, 36% of rangelands (i.e., grasses, shrubs, etc.), 12% of agricultural area, 40% of bare area, with and only 1% of the surface area covered with water. However, this cover distribution is not uniform across the region (i.e., provinces and districts) as the study area consists of diverse ecological regions. Generally, the land cover distribution is consistent with the ecoregions where extremely high altitude (>4500 m) are dominated by snow/ice and bare rocks, high altitudes (between 3000–4500 m) are dominated by grasses/shrubs (Montane grasslands and shrubs land), mid-altitudes (2000-3000 m) are dominated by temperate conifer and subtropical conifer forest, and low altitude (<2000 m) has significantly high agricultural areas relative to other elevations. Within the agricultural areas, districts with limited irrigation infrastructure have decreased crop areas. The overall decrease in agriculture in such areas is approximately 30% over the last two decades. Most of the reduction is observed in Bannu (70%), Abbottabad (60%) and Swatand (40%). However, areas with good irrigation infrastructure show an increase in agriculture areas, with an overall 18% increase over the last two decades. The highest increase is observed in Nowshera (35%), Malakand (14%) and Bajour (8%). The Federally Administered Tribal Areas (FATA) also show a significant increase in agricultural area during this time.

Table 2. Time series land cover statistics of Azad Jammu and Kashmir (AJK) and Gilgit-Baltistan (GB).

			AJK					GB		
Land Cover	1990	2000	2010	Change 1990–2000	Change 2000–2010	1990	2000	2010	Change 1990–2000	Change 2000–2010
DCF	171,149	169,521	167,689	-1628	-1832	45,226	44,248	41,800	-978	-2448
SCF	112,300	112,585	112,971	285	386	82,367	82,258	79,454	-109	-2804
DMF	90,731	89,811	87,182	-920	-2629	27,489	27,860	26,189	371	-1671
SMF	28,165	28,093	29,850	-72	1757	10,828	10,295	10,788	-532	493
DBF	31,902	30,926	30,478	-976	-448	2	2	2	0	0
SBF	25,320	26,061	25,720	741	-341					
GS	264,641	283,624	265,091	18,983	-18,533	837,438	986,354	1,022,002	148,916	35,649
P						353,995	577,378	603,743	223,383	26,365
AG	3738	12,577	12,124	8839	-453	6126	26,263	24,785	20,137	-1477
AC	244,013	199,687	243,158	-44,326	43,471	80,045	50,979	81,193	-29,066	30,215
AF	8902	75,066	41,127	66,165	-33,940	38,852	69,787	14,069	30,936	-55,718
BSR	94,742	117,154	116,083	22,412	-1071	2,427,343	3,115,546	3,024,594	688,203	-90,953
SGI	86,161	34,621	33,338	-51,540	-1283	2,962,873	1,877,379	1,934,108	-1,085,493	56,729
W	25,727	7765	22,681	-17,962	14,916	19,631	23,864	29,485	4233	5621
	1,187,492	1,187,492	1,187,492			6,892,214	6,892,214	6,892,214		

**Table 3.** Time series land cover statistics of KP and the overall study area.

KP						Total (AJK + GB + KP)				
Land Cover	1990	2000	2010	Change 1990–2000	Change 2000–2010	1990	2000	2010	Change 1990–2000	Change 2000–2010
DCF	567,035	543,111	499,617	-23,924	-43,494	783,410	756,880	709,106	-26,530	-47,774
SCF	330,536	330,565	334,134	29	3569	525,202	525,408	526,559	205	1151
DMF	328,145	318,358	309,457	-9787	-8901	446,365	436,030	422,829	-10,336	-13,201
SMF	163,148	158,708	159,254	-4440	546	202,141	197,097	199,892	-5044	2796
DBF	89,985	84,332	82,262	-5653	-2070	121,889	115,260	112,742	-6629	-2518
SBF	155,347	155,793	155,325	446	-468	180,667	181,854	181,045	1187	-809
GS	1,974,390	1,983,299	2,122,648	8909	139,349	3,076,469	3,253,277	3,409,741	176,808	156,464
P	50,518	77,983	84,943	27,465	6960	404,513	655,361	688,686	250,848	33,325
AG	58	458	448	400	-10	9922	39,298	37,358	29,376	-1940
AC	1,470,512	1,074,197	1,438,651	-396,315	364,454	1,794,570	1,324,863	1,763,003	-469,707	-217,551
AF	254,930	760,260	295,761	505,330	-464,499	302,683	905,114	350,957	602,430	212,493
BSR	4,021,609	3,921,842	4,226,359	-99,767	304,517	6,543,694	7,154,542	7,367,035	610,848	438,140
SGI	687,802	674,120	401,124	-13,682	-272,996	3,736,836	2,586,121	2,368,570	-1,150,715	-554,157
W	73,587 10,167,602	84,576 10,167,602	57,619 10,167,602	10,989	-26,957	118,947 18,247,309	116,205 18,247,309	109,786 18,247,309	-2742	-6420

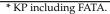
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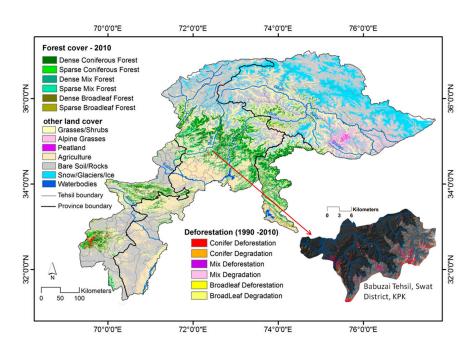
#### 3.2. Forest Cover Distribution and Change Patterns

Interpretation of the land cover images acquired in 2010 revealed that approximately 12% (2,152,173 ha) of the study area is forested. Within this total forest cover, 57% belongs to Coniferous Forest, 14% belongs to Broadleaf Forest and 29% belongs to the transition zone as Mix Forest. In terms of forest cover density, 58% of the forest has a dense canopy, whereas 42% of the area has a sparse canopy. There are high variations of forest cover distribution across the landscape. AJK has the highest percentage of forest cover, which mostly comes under the Himalayan moist temperate mix forest with dominating species of *Pinus wallichiana*, *Abies pindrow* and *Cedrus deodara*. The KP province has the largest area of forest cover, which covers a broad range of forest types including dry temperate, sub tropical pine forests and moist temperate as the most dominant forest types. GB has the smallest forest cover area among all the administrative units of the study, as a large area belongs to alpine steppe and permanent snow, whereas the major forested area comes under the dry temperate zone where *Pinus wallichiana* (Blue pine) is the dominant species (Table 4, Figure 2).

	Total Area	Forest Cover				Forest Cover Change				
Province		1990	2000	2010	2010%	Deforestation	Degradation	Regeneration	Net Change	Annual Rate (%)
KP *	10,167,602	1,634,196	1,590,867	1,540,049	15.1	112,118	35,108	9974	137,252	-0.42
GB	6,892,214	165,912	164,664	158,233	2.3	7680	2701	2	10,379	-0.31
AJK	1,187,492	459,567	456,997	453,890	38.2	6965	6113	1288	11,789	-0.13
Total	18,247,309	2,259,675	2,212,528	2,152,173	11.8	126,762	43,922	11,264	170,684	-0.38

**Table 4.** Change of forest cover (area in ha).



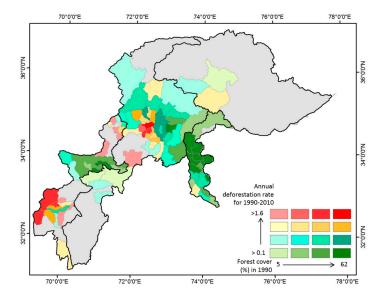


**Figure 2.** Land cover distribution and deforestation.

The current study provides spatially and temporally differentiated forest cover changes for 137 sub-districts (Tehsils) for two time periods: 1990–2000 and 2000–2010. Based on the extent of forest cover and the respective deforestation rates in each sub-district, the deforestation hotspots have been identified (Figure 3) and the top three degraded sub-districts are ranked within each administrative unit (Figure 4). In terms of forest types, dry temperate forests in the Malakand area and sub-tropical forest in the Waziristan area are under severe threat. In terms of elevation, broadleaf forests mainly

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occur between 1000–2500 m, with deforestation occurring at approximately 2000 m, whereas coniferous forest primarily occur between 1500–3500 m, with deforestation occurring at approximately 3000 m (Figure 5).



**Figure 3.** Bivariate map identifying deforestation hotspots by showing forest cover and deforestation rate for Tehsils (sub-districts) having more than 5% forest cover in 1990.

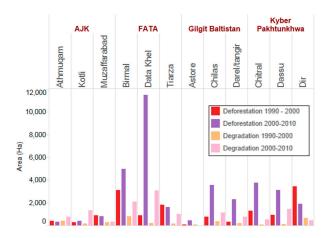


Figure 4. Most deforested sub-districts in terms of administrative unit.

Regarding deforestation during the two time periods, a total forest loss of 74,613 ha occurred during 1990–2000 and a larger total forest loss of 95,598 ha occurred during 2000–2010. A substantial portion of the deforestation during the second period occurred from the tribal areas of Waziristan. Indeed, 9786 ha of loss was observed during 1990–2000, and 30,992 ha of loss was observed during 2000–2010. In some cases, the deforestation rate has decreased during the second period of assessment, which mainly includes North Waziristan, Upper Dir and Bajor. It is also observed that during the second period of assessment the deforestation patches persist around the administrative boundaries at both the international and district levels (Figure 6), which can be attributed to ambiguity in unclear jurisdictions between the forests. Concerning the inter-class changes, most of the deforested areas have transformed into grasses/shrubs and a very small fraction of broadleaf forest areas have become agricultural land. It is also evident that thinning of dense forest (*i.e.*, conversion of dense forest into sparse forest) is also high, along with the complete destruction of forests.

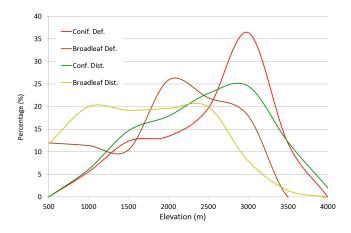
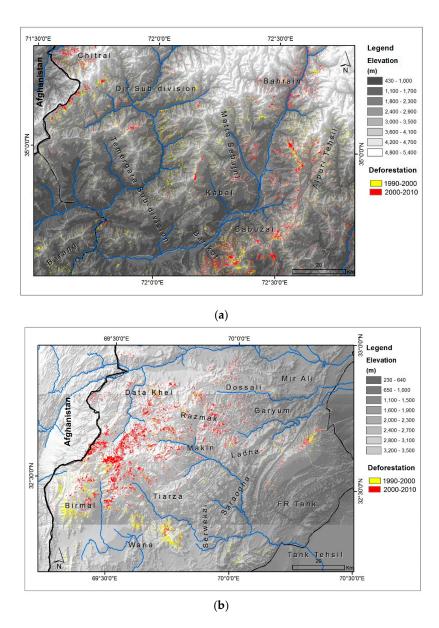


Figure 5. Forest cover and deforestation distribution as a function of elevation.



**Figure 6.** Spatial and temporal patterns of deforestation across two major forest types (a) Dry temperate forest in the KP; (b) Sub tropical forest in Federally Administered Tribal Areas (FATA).

#### 3.3. Accuracy and Validation

In addition to a thorough review by national experts the final 2010 land cover map, an assessment of the systematic accuracy of this work was performed. Error matrices were used to assess the classification accuracy and are summarized in Table 5 for the year 2010.

Class	Reference Total	Classified Totals	Number Correct	Producer Accuracy	User Accuracy
Dense Forest	21	18	17	80.95%	94.44%
Sparse Forest	28	21	20	71.43%	95.24%
Grass/Shrubs	77	51	38	49.35%	74.51%
Agriculture	49	53	32	65.31%	60.38%
Bare soil/rocks	48	66	39	81.25%	59.09%
Snow/Glaciers	56	64	34	60.71%	53.13%
Water	8	14	9	112.50%	64.29%

**Table 5.** Summary of the gridded systematic assessment results.

Because the land cover exercise was focused on the interpretation of forest cover, good accuracy is achieved for the forest classes. Regarding the non-forest cover classes, the accuracy was generally low because of high intra-annual (seasonal) variability of land cover classes of grasses, agriculture and snow cover. With the availability of high-resolution time series Google Earth images, it was possible to validate deforestation patches during 2000–2010 (Table 6). A visual example of this validation process is given in Figure 7.

**Table 6.** Validation summary of deforestation/degradation patches between 2000–2010 using Google Earth (GE) images.

		Patches > 5 ha	Patches > 1 & < 5 ha			
Class	Total # of Patches	# of Patches Found on GE	Accuracy (%)	Total # of Patches	# of Patches Found on GE	Accuracy (%)
DCF	274	102	91	1826	550	83
SCF	286	97	80	3,807	1,200	84
DMF	124	40	90	1,236	400	88
SMF	73	25	84	1,177	300	86
DBF	80	25	92	404	150	81
SBF	170	60	92	1,314	400	81

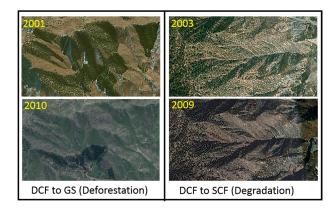


Figure 7. An example of the validation of deforestation and degradation based on Google Earth images.

#### 4. Discussion

The time series land cover mapping (1990, 2000, 2010) revealed that extensive deforestation/ degradation is occurring in the area. Indeed, approximately 170,684 ha of forest was cut or severely degraded during this time period (Tables 2-4). The increase in the sparse forest classes during the study period is primarily attributed to a shift from the dense forest classes to sparse forest classes (degradation). Overall, the AJK state has the lowest deforestation rate, where the demand for wood for fuel, which is driven by population growth, is attributed to be the primary cause of this deforestation [55]. KP province has the highest deforestation, which is also linked with population growth for fuel wood and further aggravated by large scale illegal commercial harvesting [56]. In addition, recent security conflicts in the western borders have worsened this situation [57]. Several reports relate this deforestation with nexus of timer mafia and combatant groups for financial gains and clearing by security forces for tactical reasons [58–60]. Deforestation along the western borders of Pakistan during last decade are similar to the deforestation patterns in Afghanistan during 1980–2000 and the spatially concentrated loss and heavy dependence on forest resources during the Rwandan conflicts [61,62]. The deforestation and degradation levels reported in this study need to be analyzed in terms of anthropogenic factors as reported in several other studies [55–61]. Similarly, no specific studies exist on assessing the impact of natural factors like climate, water, landslides, disease, etc., on forest loss in the mountain region of Pakistan. The quantitative assessments on underlying causes of deforestation using spatial and temporal patterns of deforestation and degradation can further help in managing forest resources more effectively.

When a province-wide comparison is made between the current assessment and previous national forest cover change assessments [47,63], major differences in the extent of forest cover and deforestation rates are observed (S2, Table S8-S11, Supplementary material). In its assessment, reference [47] delineates forest area to be 660,000 ha for the Gilgit-Baltistan province in 1990, which is 9.4% of its total area. However, most of the province (78%) is above 3600 m elevation with limited annual rainfall (average 120–240 mm). Thus, the prevailing bio-climatic conditions cannot support such large areas of forest, as described in reference [47]. In past inventories, such errors in assessment can be attributed to limited data and image interpretation as well as the use of inconsistent methods. Similarly, references [64,65] describe the drawbacks of global algorithms and datasets [63] for local level assessments. In the current study, the assessment is based on uniform data, methods and interpretations. Overall, the annual forest cover rate of change is -0.38% for the entire area, and there are significant differences in the deforestation rates within the provinces. We note that this overall deforestation rate is inconsistent with the records from international organizations, which state a severe annual deforestation rate of approximately 2%. This study suggests that the international figures are based on site-specific studies, which are mostly conducted within deforestation hotspot areas (Figure 3) that cannot be accurately extrapolated to the entire landscape. In such local level assessments, the recent temporal forest cover analysis (1968, 1990, 2007) revealed annual deforestation rates of 1.86%, 1.28%, and 0.80% in three zones of Scrub forest, agro-forest and alpine forest, respectively, in the Swat district [66], whereas reference [28] observed an annual gross deforestation of 0.81% in the Swat and Shangla districts of KP province during 2001–2009. Further, reference [56] observed an annual forest cover rate of change of -1.32% during 1996-2008 in the Malakand and Hazara regions. In long period assessments [8], Schickhoff (1995) observed 50% forest loss in the Kaghan Valley (in the Khyber Pakhtunkhwa province) from 1847 to 1990. He noted that deforestation was high mainly during two time periods; the first occurred from 1847 to 1867 (i.e., the first two decades of British rule) and the second occurred during the Second World War in the 1940s. In the Siran Valley, reference [67] identifies 45% forest loss between 1979 and 1988 when a large population of Afghan refugees resettled in this area. Additionally, reference [68] observed approximately 50% forest cutting in the Basho Valley from 1968 to 2002, which was attributed to illegal commercial harvesting aggravated by political and administrative constraints.

According to reference [69], deforestation in northern Pakistan is occurring primarily because of institutional neglect and there is a need to implement proper forest management strategies. According to reference [70], historical analysis complemented with satellite images highlights the role of resource rights in forest protection. Specifically, the disconnect between de jure and de facto resource rights has contributed to extensive deforestation over time. The study emphasizes the need to define these rights more clearly, to implement community management systems and to formalize these rights within a legal framework. Considering the on-going demand for wood for fuel [48], it is possible that the forests in Malakand and Hazara will cease to exist by 2027. Supplies from plantation, agricultural and range lands will only cover 21% of the total demand at this point in time, and an uncovered demand/supply gap of 8.8 million m<sup>3</sup> by 2027 will continue to grow to 13.6 million m<sup>3</sup> by 2050, of which again only 21% can be covered by local woody bio-mass supplies. In this timber demand situation, a decrease in agricultural areas and reductions in populated lands may also bear witness to small-scale tree cutting as an income-generating activity [56]. Reference [71] observed immense deforestation caused by excessive fuel-wood consumption in the Bagh district of Azad Jammu and Kashmir. There are not enough studies exist on associating massive forest loss in mountain region of Pakistan with natural factors like climate, water, landslides, disease, etc.

The observed destruction of forest eco-systems may result in environmental and bio-diversity degradation with loss of function of related ecosystem services such as soil conservation, carbon sequestration and recreational potential. The losses caused by Himalaya's degradation are not confined to the region itself but also seriously affect the environment and economy of the adjoining plains of the Indus basin through disturbances in the hydrological cycle, which contribute to soil erosion, siltation, floods and desertification. The incidence of floods in the Indus river system has been more severe and more frequent over the past 25 years than during the previous 65 years, primarily because of increased surface runoff and accelerated erosion in the Himalayan mountains [72]. According to the Pakistan Water Strategy, the country needs to raise water storage of 18 million acre-feet (MAF) by 2050, where 30% of this figure is only to replace storage loss caused by siltation.

The current study is the first systematic effort to characterize forest cover mapping and deforestation assessment of 60% of the forested areas of Pakistan. The results from this study will provide important insight to the deforestation patterns, which will facilitate the development of appropriate forest conservation and management strategies within the country. Careful analysis of these results may provide insights into land-change dynamics, both its causes and consequences, and identify deforestation hotspots. Moreover, the statistics available at the local administrative unit can provide the basis for the regular monitoring of deforestation in the area.

In terms of limitations of the study, the steep terrain posed some challenges in interpreting the forest and its change in shadowed areas. No deforestation has been marked in such situations, which represents the most conservative (unexaggerated) estimate of deforestation. Also, given the slow growth in these forest areas, and thus poor detectability, forest gains were less apparent than losses.

# 5. Conclusions

This study provides deforestation and degradation statistics in Pakistan, for a period of 20 years using consistent set of methods and datasets. The results show a significant increase in deforestation/degradation between 1990–2000 and 2000–2010, increasing from 75,000 ha to 95,000 ha. The study, being the first large area assessment, also contributes in clarifying gross exaggeration of deforestation rate being reported based on inconsistent localized assessments conducted in the severely degraded areas. The deforestation hotspots identified in the current study needs to be explained in context of underlying drivers of change. The quantitative assessments on underlying causes of deforestation using spatial and temporal patterns of deforestation can further help in devising forest management policies more effectively. This is a subject that would merit more attention in future works.

**Supplementary Materials:** The following are available online at www.mdpi.com/2072-4292/8/5/385/s1: Table S1: List of satellite data used, S1: Summary of decisions for improving the interpretation of land cover, Tables S2–S7: Land cover change matrix, S2: Comparison with other studies in the area. Table S8: Comparison of current assessment with global assessment [1]. Tables S9–S11: Comparison of current assessment with previous national assessment [2] for Khyber Pakhtunkhwa (KP) including FATA, Gilgit-Baltistan (GB), and Azad Jammu and Kashmir (AJK).

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**Author Contributions:** Faisal M. Qamer took the lead on designing, undertaking the assessment, and writing the manuscript. Khuram Shehzad contributed with the geospatial data pre-processing, image classification and writing the manuscript. Sawaid Abbas helped design and summarize resulting data. MSR Murthy, Birendra Bajracharya and Chen Xi helped design, provided oversight of overall assessment and contributed in the manuscript writing. Hammad Gilani contributed significantly to the discussion of results.

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