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Remote sensing analysis of spatiotemporal impacts of anthropogenic influence on mountain landscape ecology in Pir Chinasi national park

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Mountain landscapes can be fragmented due to various human activities such as tourism, road construction, urbanization, and agriculture. It can also be due to natural factors such as flash floods, glacial lake outbursts, land sliding, and climate change such as rising temperatures, heavy rains, or drought. The study's objective was to analyze the mountain landscape ecology of Pir Chinasi National Park under anthropogenic influence and investigate the impact of anthropogenic activities on the vegetation. This study observed spatiotemporal changes in vegetation due to human activities and associated climate change for the past 25 years (1995–2020) around Pir Chinasi National Park, Muzaffrabad, Pakistan. A structured questionnaire was distributed to 200 residents to evaluate their perceptions of land use and its effects on local vegetation. The findings reveal that 60% of respondents perceived spatiotemporal pressure on the park. On the other hand, the Landsat-oriented Normalized Difference Vegetation Index (NDVI) was utilized for the less than 10% cloud-covered images of Landsat 5, 7, and 8 to investigate the vegetation degradation trends of the study area. During the entire study period, the mean maximum NDVI was approximately 0.28 in 1995, whereas the mean minimum NDVI was -2.8 in 2010. QGIS 3.8.2 was used for the data presentation. The impact of temperature on vegetation was also investigated for the study period and increasing temperature trends were observed. The study found that 10.81% (1469.08 km²) of the area experienced substantial deterioration, while 23.57% (3202.39 km²) experienced minor degradation. The total area of degraded lands was 34.38% (or 4671.47 km²). A marginal improvement in plant cover was observed in 24.88% of the regions, while 9.69% of the regions experienced a major improvement. According to the NDVI-Rainfall relationships, the area was found to be significantly impacted by human pressures and activities ($r \leq 0.50$) driving vegetation changes covering 24.67% of the total area (3352.03 km²). The area under the influence of climatic variability and change ($r \geq 0.50 \geq 0.90$) accounted for 55.84% (7587.26 km²), and the area under both climatic and human stressors ($r \geq 0.50 < 0.70$) was 64%. Sustainable land management practices of conservation tillage, integrated pest management, and agroforestry help preserve soil health, water quality, and biodiversity while reducing erosion, pollution, and the degradation of natural resources. landscape restoration projects of reforestation, wetland restoration, soil erosion control, and the removal of invasive species are essential to achieve land degradation neutrality at the watershed scale.

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Vegetation is an essential component of the biological cycle. Vegetation trends highlight changes in ecological systems and help determine the best strategies for mitigating climate change. Highlighting the changes in vegetation due to anthropogenic activities as well as climate change is essential for improvement. An important topic in the study of the local ecological environment is the components of the ecosystem represented by vegetation under the effect of anthropogenic activities¹. The dynamics of regional vegetation have a substantial impact on ecological security², ecosystem services and, are frequently used as important indicators of ecological variations in the environment³. As human activity has risen in recent decades, alterations in vegetation has deeply captured the trails of human activity, which have been made worse by climate change^{4,5}. Anthropogenic stresses are thought to have significant effects on vegetation and ecosystem services as we go through the Anthropocene^{6,7}. The global ecosystem is now changing as a result of climate change and land cover variations, which are identified as key influences on the dynamics of vegetation under universal change. Numerous anthropogenic stresses along with climate change are causing vegetation to alter and degrade in highland locations, which further compromises the ecosystem services provided by mountains and the way of life of a small number of mountain people. In the realm of research on global change, understanding the linkages between natural vegetation and cultivated vegetation has been a crucial problem that is receiving more and more attention from the scientific community⁸. To investigate the change in vegetation, Normalized Difference Vegetation Index (NDVI) is mostly recommended^{1,9,10}. Utilizing the NDVI, a surrogate technique for the greenness of landscape and biological dynamics of change has made satellite Remote Sensing (RS) of vegetation simple^{1,9,10}. The investigation of vegetation status under changing climatic patterns and the tracking of the ecological environment's quality relies heavily on the monitoring and assessment of NDVI changes in vegetation¹¹. Limited research examined how vegetation dynamics relate to both human activity and climate change^{1,12–21}. Moreover, residents of these mountains can better highlight the changes in vegetation that occurred due to human intervention as well as climate change^{22–24}. The objective of this study was to understand the mechanisms behind grassland degradation of Pir Chinasi National Park and managing damaged grasslands, which needs quantitative assessments of the relative effects of anthropogenic activity and climate change on grasslands²⁵. As for the significance of the mountain, the UN 2030 Sustainable Development Agenda has included targets for protecting and sustainably developing mountain ecosystems²⁶. The cover index (SDG 15.4.2) of the mountain forests of Pir Chinasi National Park has been utilized as a first approximation for measuring the sustainability and protection of mountain habitats as well as the progress made towards the aforementioned aim.

Study area

As the heights vary from roughly 700 m Above Sea Level (ASL), the Pir Chinasi National Park in the Muzaffarabad (Fig. 1) neighborhood exhibits a topographic variety²⁷. The study area's height is 2900 m (9,500 ft)²⁸. The area has natural beauty with its dense trees, swiftly flowing rivers, and twisting streams. The mean extreme temperature for January and June respectively, ranged from -2.6 °C to 45.2 °C. The average rainfall is found to be between 1000 and 1300 mm or around 680 mm and falls over the four months from May to August. During the day, the wind blows from west to east, while at night, it blows from southeast to north and the wind is brisker in the afternoon. The area of Pir Chinasi is found to be dry Subtropical type in which *Acacia modesta*, *Olea ferruginea*, and Chir Pine are the most dominant tree species in the area²⁹. The vegetation of the area is comprised of a spacious variety of herbs, trees, climbers, and shrubs. The ground cover is comprised of a wide variety of angiosperms, mosses, and ferns.

The western Himalayan region, a biodiversity hotspot, is impacted in several ways by anthropogenic climate change. Due to the great seasonality of the western Himalayan region, including the Muzaffarabad district, investigations on the interactions between the timing of phenological periodic occurrences and climatic seasonality are important. The different land users of Pir Chinasi National Park benefit from the area's natural resources and environment. During dry seasons, herders who live on the mountain frequently light fires to encourage the growth of forage for cattle grazing. This study assesses the dynamics of vegetation degradation during five years (1995–2020). This serves as the baseline information for tracking the watershed-level progress towards the objectives and pathways of SDGs 15.3.1 and 15.4.2 related to land degradation neutrality.

Materials and methods

Data collection

This study was conducted in Pir Chinasi National Park, Muzaffarabad, Kashmir, Pakistan. Pir Chinasi National Park is a tourist spot, and many tourists visit this area annually. A one-shot Household Survey (HHS) was conducted from 200 residents using convenient sampling in this study. It was a hilly area with a scattered population, so it was difficult to collect a larger sample size. A team of enumerators and the chief investigator spoke with the heads of the families. Family members were contacted in case of the unavailability of the head of household. The purpose of each question of the survey was explained to the respondents. Participants were provided with informed consent, and they were informed of the study's advantages, goals, and financing. All surveys were conducted following the shared research principles and ethics. The survey asked about households' occupation, age, gender, education, environmental harm to vegetation, and government support. Moreover, plants/seeds were handled under the direct supervision of Dr. Naem Ahmed, National University of Modern Languages, Islamabad-Pakistan following the proper national and international strategies.

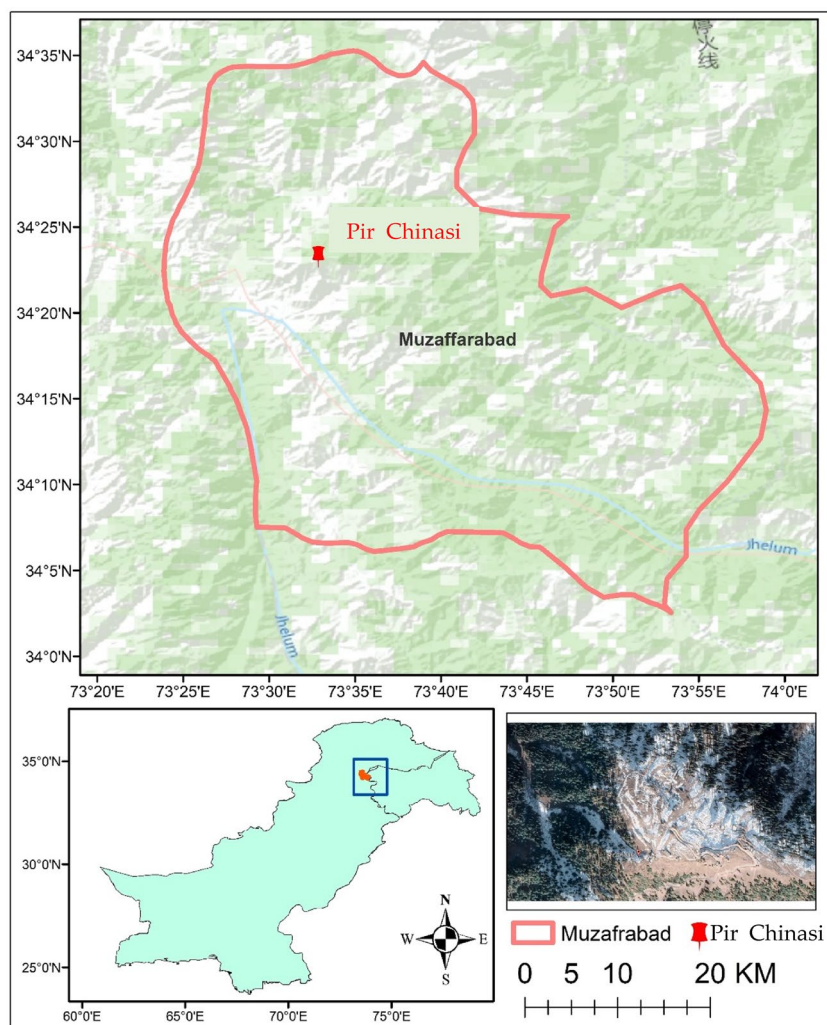


Fig. 1. Location map of the Pir Chinasi National Park, Muzaffarabad (District of Azad Jammu & Kashmir). The map was created using ArcGIS Desktop software (version 10.8.2, Esri Inc., Redlands, CA, USA).

Data processing

The authors confirmed that the collection and execution of the experiment complied with the IUCN statement on research, involving species at risk of extinction and by the convention on the trade in endangered species of wild fauna and flora. For data collection, Google Forms were utilized and for data processing and analysis, SPSS was used. All methods were performed following the relevant guidelines and regulations.

To investigate the effects of human activities on the flora and ecology of the area, Remote Sensing (RS) and Geographic Information System (GIS) techniques and datasets have been utilized in Table 1. RS and GIS

Scene ID	Date of acquisition	Sensor	Resolution
LT05_L2SP_150036_19950508_20200913_02_T1	08. 05. 1995	Landsat 5	30 m
LE07_L2SP_150036_20000411_20200918_02_T1	11. 05. 2000	Landsat 7	30 m
LE07_L2SP_150036_20050527_20200914_02_T1	27. 05. 2005	Landsat 7	30 m
LE07_L2SP_150036_20100509_20200911_02_T1	09. 05. 2010	Landsat 7	30 m
LC08_L2SP_150036_20150515_20200909_02_T1	15.05.2015	Landsat 8	30 m
LC08_L2SP_149035_20201015_20211025_02_T1	15. 05. 2020	Landsat 8	30 m
LC08_L2SP_149035_20211015_20211025_02_T1	15. 05. 2021	Landsat 8	30 m
LC08_L2SP_150036_20200512_20200820_02_T1	12.05.2020	Landsat 9	30 m

Table 1. Landsat satellite imagery of the years 1995 to 2020. ^aTropical Livestock Units (TLU).

techniques datasets were proven excellent for large areas and difficult terrain^{30,31}. It was difficult to collect data manually in such an area; hence, remote detection and data collection are more appropriate and easier.

Landsat data

Landsat imagery is an efficient data source for analyzing mountain landscapes, particularly difficult terrain because of its wide and remote coverage. In this study, Landsat 4/5 Thematic Mapper (TM), 7 Enhanced Thematic Mapper Plus (ETM+) & 8 Operational Land Imager (OLI) data were utilized for the temporal analysis and vegetation indices analysis. Multiple Landsat images were downloaded from the official website of USGS (www.usgs.gov).

The spatial resolution of Landsat 7 is 30 × 30 m, the revisit time of the satellite is 16 days whereas, the swath width of the satellite is 185 km. Researchers used this data in different kinds of studies due to its large area coverage, fine resolution, and result accuracy, therefore in this study, Landsat data was selected to be used.

Digital elevation model

The Digital Elevation Model (DEM) is an effective mode of 3D representation of the earth's surface. DEM with a spatial resolution of 30m is utilized for ground elevation estimation. DEM of 30-m resolution have been utilized in the study to check the elevation and Slope of the area. Elevation and slope affect the LULC of the area, therefore 30-m resolution was sufficient for the required analysis. DEM data is freely available on the official website. Data is freely available and can be downloaded from the official website of Earth Explorer.

After data collection from the various websites, data was segregated and compiled for analysis. The study area was analyzed for the twenty-five years from 1995 to 2020 and time series data was collected with a five-year gap e.g. (1995, 2000, 2005, 2010, 2015, and 2020). Scan Line error (SLE) was present in Landsat 7 (2005 & 2010 Imagery). SLE was removed from the Landsat 7 imagery via the Landsat toolbox extension.

Error handling

Due to the missing data of the Scan Line Corrector (SLC) of the Landsat instrument in 2003, approximately 20 to 22% of data went missing, and gaps were generated in the imagery. This error made the image difficult to detect. Therefore, the technique of Gap-Fill proposed by the reference³² had been applied and error was removed from the 2007 and 2010 imagery.

Index calculation

Raw satellite data was collected freely from the website for further processing and calculation of the vegetation indices. The satellite data was converted from Digital Numbers (DN) to the values of the Top-of Atmospheric Reflectance (TOA). It was a two-step method (1) radiance of DN and (2) radiance to TOA^{33,34}.

Due to the presence of a Scan Line Error (SLE) in Landsat 7 DN, conversion was done manually. The conversion of Landsat 7 data to DN was presented in Eq. 1.

$$L\lambda = (\text{gain}\lambda \times \text{DN7}) + \text{bias}\lambda \quad (1)$$

In this equation where $L\lambda$ was found to be the calculated radiance [in Watts per square meter * μm * ster], DN7 was the Landsat 7 ETM+ DN data, and the gain and bias were band-specific numbers²¹. Radiance to TOA conversion was also done for Landsat 7. The reflectance could be thought of as a “planetary albedo”, or a fraction of the sun's energy that was reflected by the surface²²; Eq. (2).

$$R\lambda = \pi \times L\lambda \times d^2 E_{\text{sun},\lambda} \times \sin(\theta SE) \quad (2)$$

$R\lambda = \pi * L\lambda * d^2 E_{\text{sun},\lambda} * \sin(\theta SE)$ (3) where $R\lambda$ was the reflectance (unitless ratio), $L\lambda$ was the radiance calculated in Eq. (2), d was the earth-sun distance (in astronomical units), $E_{\text{sun},\lambda}$ was the band-specific radiance emitted by the sun, π was a constant value. The process of (TOA) was done for Landsat 8 via band 10. Thermal Infra-Red DN could be converted into TOA spectral radiance utilizing rescaling factors. A Set of equations had been used for LST calculation. DN to TOA conversion was presented in equation Eq. (3).

$$L\lambda = ML \times Q_{\text{cal}} + AL - O_i \quad (3)$$

where, $L\lambda$ = TOA spectral radiance (in Watts/(sq. meter * μm), ML = Radiance multiplicative Band No, AL = Radiance add band, Q_{cal} = DN, Q_i band correction value. The temperature was converted from Kelvin to Celsius via Eq. (4).

$$BT = \frac{K_2}{\ln\left(\frac{k_1}{L\lambda} + 1\right)} - 273.15 \quad (4)$$

Finally, NDVI was calculated. The reflectance known as NDVI, a measure of greenness and proxy for vegetation degradation, was captured (Eq. 5).

$$NDVI = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (5)$$

In this equation RED = DN value of RED band and NIR = DN value of Near-Infrared band, after that land Surface Emissivity was calculated via square of NDVI. Lastly, LST was calculated for the selected study area using Eq. 6

$$LST = \frac{BT}{1} + \left(\lambda \times \frac{BT}{c^2} \right) \times \ln(E) \quad (6)$$

In this equation $BT = TOA$, whereas, brightness in $^{\circ}C$, $\lambda =$ wavelength, similarly $E =$ Land surface Emissivity, and $C =$ velocity of light.

Results

Demographic and socioeconomic information

The data in Table 2 shows that the surveyed population is primarily composed of males (56.7%) and females (43.3%). The percentages were calculated based on the total number of respondents.

The data in Table 3 indicates that the majority of the sample respondents fell within the 18–24 years age range (60.5%), followed by smaller proportions in older age ranges. This age distribution provides insight into the demographic composition of the surveyed population and can be useful for understanding how different age groups perceive and respond to the issues related to protecting natural resources.

The data in Table 4 provides insight into the different occupational roles present within the surveyed population. The majority of respondents were students (53.5%), followed by government/private/NGO employees (18.5%) and individuals with other occupations such as housewives, the unemployed, and those involved in agriculture, livestock farming, daily wage labor, and business. This distribution can offer context for understanding how various segments of the population view and engage with natural resource protection measures.

The data in Table 5 provides insight into the educational backgrounds of the surveyed individuals. The majority had a college/university degree (59.2%), followed by postgraduate degree holders (14.0%). Smaller proportions had secondary education, primary education, or no formal education. This distribution offers context for understanding how education levels might influence perceptions and attitudes toward natural resource protection measures.

Table 6 provides insight into the household size of the surveyed individuals. The most common household sizes were those with 5–6 people (35.0%) and 7–8 people (25.5%). It is observed that the educated respondents

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Male	89	56.7	56.7	56.7
	Female	68	43.3	43.3	100.0
	Total	157	100.0	100.0	

Table 2. Gender distribution of the surveyed population.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	18–24 Years	95	60.5	60.5	60.5
	25–34 Years	20	12.7	12.7	73.2
	35–44 Years	23	14.6	14.6	87.9
	45–54 Years	9	5.7	5.7	93.6
	55–64 Years	7	4.5	4.5	98.1
	65 and above	3	1.9	1.9	100.0
	Total	157	100.0	100.0	

Table 3. Age distribution of the surveyed population.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Government/Private/NGO employee	29	18.5	18.5	18.5
	Student	84	53.5	53.5	72.0
	Housewife	8	5.1	5.1	77.1
	Unemployed	8	5.1	5.1	82.2
	Agriculture	6	3.8	3.8	86.0
	Livestock farming	10	6.4	6.4	92.4
	Daily wage laborer	5	3.2	3.2	95.5
	Business	7	4.5	4.5	100.0
	Total	157	100.0	100.0	

Table 4. The occupational distribution of the sample respondents.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Postgraduate degree or Higher	22	14.0	14.0	14.0
	College/University degree	93	59.2	59.2	73.2
	Secondary education	13	8.3	8.3	81.5
	Primary education	12	7.6	7.6	89.2
	No formal education	17	10.8	10.8	100.0
	Total	157	100.0	100.0	

Table 5. The educational distribution of the surveyed population.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	1–2	3	1.9	1.9	1.9
	3–4	30	19.1	19.1	21.0
	5–6	55	35.0	35.0	56.1
	7–8	40	25.5	25.5	81.5
	9–10	15	9.6	9.6	91.1
	More than 10	14	8.9	8.9	100.0
	Total	157	100.0	100.0	

Table 6. The distribution of the size of households of the surveyed individuals.

had more awareness about environmental degradation and the impact of anthropogenic activities. This distribution can offer context for understanding the living arrangements of the surveyed population, which might impact their resource consumption patterns and attitudes toward environmental protection.

In each group of Table 7, the frequency and percent values indicate the number and proportion of respondents involved in the specified type of agricultural activity. This data provided insights into the agricultural practices and activities of the surveyed population, showing the prevalence of different crops and livestock within their households. This information can be useful for understanding the composition of their agricultural practices and their potential impact on the environment and natural resources.

Table 8 provides insights into the purpose of agricultural activities within the sample respondents. The majority of respondents engaged in subsistence farming (49.0%), followed by those involved in both subsistence and commercial farming (38.9%), and a smaller proportion focused on commercial farming alone (12.1%). Although

Group	Crop or livestock	Frequency (N = 157)	Percent
Group 1: Crops (Wheat; Maize; Rice)	Wheat	78	49.7
	Rice	34	21.7
	Maize	37	23.6
Group 2: Vegetables and Fruits (Vegetables; Fruits)	Vegetables	56	35.7
	Fruits	51	32.5
Group 3: Livestock (Cattle; Sheep; Goats; Poultry)	Cattle	51	32.5
	Sheep	41	26.1
	Goats	54	34.4
	Poultry	40	25.5

Table 7. Distribution of different crops and livestock groups within the surveyed population.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Subsistence	77	49.0	49.0	49.0
	Commercial	19	12.1	12.1	61.1
	Both	61	38.9	38.9	100.0
	Total	157	100.0	100.0	

Table 8. Distribution of agricultural practices by the respondents.

subsistence farming contains a major share of the area, but still commercial farming has a second major share. Commercial farming uses fertilizers and pesticides which harm human health as well as deteriorate the environment. This distribution sheds light on the nature of agricultural practices within the surveyed community and how they might impact natural resource utilization and conservation efforts.

Table 9 revealed that more than half of the surveyed individuals were aware of the environmental issues in the Pir Chinasi National Park (52.9%), while the remaining respondents were not aware (47.1%). This awareness information was crucial for understanding the level of knowledge within the surveyed population about the environmental challenges in the region and can guide efforts to improve awareness and engagement in addressing those issues.

These percentages in Table 10 indicate the proportion of respondents who perceive each anthropogenic activity as a significant contributor to the depletion of natural resources in the area. The respondents' opinions pointed to deforestation, road construction, livestock grazing, and tourism as the main activities causing resource depletion, with varying levels of consensus among the surveyed population. This information can be valuable for understanding the perceived drivers of environmental degradation and a reference³⁵ can help guide strategies for mitigating these activities to ensure sustainable resource management³⁶.

Table 11 indicates the varied perceptions within the surveyed population regarding the impact of climate change on the natural resources of the Pir Chinasi National Park. Responses ranged from highly negative to highly positive, with a significant portion of respondents expressing a somewhat negative perception. These responses provide insight into the diverse perspectives on the potential consequences of climate change on the local environment and resources³¹.

The percentages in Table 12 indicate the proportion of respondents who utilize each type of fuel for cooking and heating purposes. The data provides insights into the fuel preferences within the surveyed community, which have significant implications for energy consumption patterns and their potential environmental impact. The use of firewood, LPG, natural gas, and electric heaters appears to be relatively common among the surveyed population³⁷.

Table 13 reveals that a significant portion of the surveyed population did not have access to alternative sources of energy, such as solar power (65.0%), while a minority did have access (35.0%). This information provides

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	83	52.9	52.9	52.9
	No	74	47.1	47.1	100.0
	Total	157	100.0	100.0	

Table 9. Awareness of the surveyed population regarding environmental issues in the Pir Chinasi National Park.

Anthropogenic activities	Frequency	Percent
	(N = 157)	
Deforestation	114	72.6
Road construction	68	43.3
Agriculture	30	19.1
Livestock grazing	43	27.4
Tourism	62	39.5

Table 10. Respondents' opinions about anthropogenic activities causing the depletion of natural resources in Pir-Chinasi.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Highly negative	29	18.5	18.5	18.5
	Somewhat negative	38	24.2	24.2	42.7
	Somewhat positive	44	28.0	28.0	70.7
	Somewhat positive	11	7.0	7.0	77.7
	Highly positive	3	1.9	1.9	79.6
	Total	157	100.0	100.0	

Table 11. Perceptions of respondents about the impact of climate change on the natural resources of the Pir Chinasi National Park area.

Fuel for cooking and heating	Frequency (N = 157)	Percent
Firewood	77	49
Charcoal	16	10.2
LPG	47	29.9
Natural Gas	54	34.4
Kerosene	08	5.1
Electric Heater	17	10.8

Table 12. Types of fuel used for cooking and heating within the surveyed population.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Yes	55	35.0	35.0	35.0
	No	102	65.0	65.0	100.0
	Total	157	100.0	100.0	

Table 13. Accessibility of alternative sources of energy, such as solar power, within the surveyed population.

insights into the availability and adoption of renewable energy solutions within the surveyed community^{36,37}, which can have significant implications for energy security, environmental sustainability, and quality of life.

Table 14 provides insights into the livestock ownership patterns within the surveyed community. The majority owned 1–5 animals (43.9%), with smaller proportions owning 6–10 animals (17.2%) and 11–20 animals (7.6%). A small percentage owned more than 50 animals (1.3%), and a significant proportion did not own any livestock (29.9%). This distribution offers an understanding of the diversity in livestock ownership and its potential implications for resource use and management.

Table 15 provides insight into where the surveyed individuals' livestock are allowed to graze. The responses indicated that animals were allowed to graze on private land (26.1%), common land (27.4%), and forests (17.2%), while a notable percentage did not have animals that graze (29.3%). Understanding the locations where livestock is grazed can help assess the potential impact on these areas and inform resource management strategies.

Table 16 reveals that a majority of the surveyed population had observed changes in the natural resources of the Pir Chinasi National Park area over the past 5–10 years (59.9%), whereas a smaller proportion (40.1%) has not perceived such changes. This information provides insights into the perceived dynamics of natural resource changes in the region and can help in understanding the evolving environmental conditions and potential factors contributing to these changes.

The percentages in Table 17 indicate the proportion of respondents who believed that each measure should be taken to protect the natural resources in the area. It appears that reforestation programs had the highest agreement (58.0%), followed by strict enforcement of environmental protection laws (53.2%). Other measures

		Frequency	Percent	Valid percent	Cumulative percent
Valid	1–5 (TLU ¹)	69	43.9	43.9	43.9
	6–10 (TLU)	27	17.2	17.2	61.1
	11–20 (TLU)	12	7.6	7.6	68.8
	More than 50 (TLU)	2	1.3	1.3	70.1
	N/A	47	29.9	29.9	100.0
	Total	157	100.0	100.0	

Table 14. Livestock animals within the surveyed population. *TLU* tropical livestock units

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Private land	41	26.1	26.1	26.1
	Common land	43	27.4	27.4	53.5
	Forests	27	17.2	17.2	70.7
	N/A	46	29.3	29.3	100.0
	Total	157	100.0	100.0	

Table 15. Locations where the surveyed population's animals are allowed to graze.

		Frequency	Percent	Valid percent	Cumulative percent
Valid	Yes	94	59.9	59.9	59.9
	No	63	40.1	40.1	100.0
	Total	157	100.0	100.0	

Table 16. Perceptions of the surveyed population about any changes in the natural resources (forests, soil, water, and biodiversity) in the Pir Chinasi National Park area over the past 5–10 years.

Additional measures should be taken to protect the natural resources	Frequency (N = 157)	Percent
Strict enforcement of environmental protection laws	84	53.2
Reforestation programs	91	58
Sustainable agriculture practices	44	28
Sustainable tourism practices	56	35.7
Public awareness campaigns	76	48.7
Collaboration with local communities	57	36.3

Table 17. Opinions of the surveyed population on additional measures that should be taken to protect the natural resources in the Pir Chinasi National Park area.

such as public awareness campaigns, collaboration with local communities, sustainable tourism practices, and sustainable agriculture practices also received notable support from the surveyed population. These opinions provide insight into the potential strategies that could be pursued to safeguard the natural resources in the Pir Chinasi National Park area according to the surveyed community.

NDVI

Time series analysis of vegetation change dynamics of the selected area was evaluated via NDVI. Spatial and temporal dynamics of vegetation degradation, depending on the time scale were analyzed. The status of the landscape was reflected in vegetation indices (VIs), and their interpretation across time explained patterns in vegetative greening (land improvement) and browning (land deterioration). Based on a long-term investigation of vegetation dynamics, Figs. 2–4 illustrate swings between periods of gradual deterioration and minor improvements (greening). A slightly declining trend of NDVI was observed during the study period (1995–2020). During the entire study period mean NDVI (maximum = 0.28 (1995)/minimum = 2.8 (2010) was identified see Fig. 2 for instance. In 2000, mean NDVI was monitored at 0.24 (Fig. 2b). Similarly, the NDVI of 2005 was also calculated via the set of formulas mentioned in the materials and method Section^{38–40}.

The mean value of NDVI was 0.22 to 0.76. Pir Chinasi National Park was known for tourism, this decline can be attributed to the expansion of built-up areas to accommodate growing tourist demands, leading to habitat loss and ecological changes. This decline can be attributed to the expansion of built-up areas to accommodate growing tourist demands, leading to habitat loss and ecological changes. NDVI for the year 2015 and 2020 was observed 0.07–0.53 to 0.08–0.57 (Fig. 2e and f).

Land surface temperature (LST)

Surface temperature had a significant impact on the local ecology and biodiversity. Therefore, in this study, LST for the study period was also calculated to investigate the impacts of temperature on vegetation. The temperature was estimated via Landsat imagery for the selected images from 1995 to 2020 (Fig. 4). The temperature range for 1995 was 19 minimum to 29° C maximum (Fig. 4a), 23° to 36° for 2000 (Fig. 4b), whereas 21° to 35° temperature range was observed for 2005 (Fig. 4c). 29° C to 39° C for 2010 see Fig. 4d. For the year 2015 and 2020 (9°–26° C and 17–37° C) were observed respectively.

It has tools specifically for slope calculation, where the slope can be expressed in degrees or as a percentage. Slope analysis, spatial analysis, and 3D visualization using extensions like Spatial Analyst or 3D Analyst. User-friendly interface, extensive documentation, and strong support for various geospatial analyses.

Ground truthing

Data collection from the field was time-consuming due to the monetary constraints^{23,24,33}, therefore, Google Earth data was utilized for the investigation of urbanization patterns. Deforestation was observed where recreational activities were occurring, see Fig. 5.

Figure 5 highlighted the ground truthing based on detailed information about vegetation to validate the remote sensing. The figure shows urbanization patterns. Ground truthing with physical sampling strengthened the validation of the NDVI analysis. Map was generated using the open-source software (QGIS 3.8) along with that an open-source software Google Earth Pro (GEP) was utilized for image data collection. KML files were generated using GEP and converted into shapefiles in the QGIS environment. The geographical coordinates (34°23'22"N 73°32'57"E) were used. <https://earth.google.com/web/search/Pir+Chinasi/@34.38987286,73.55007>

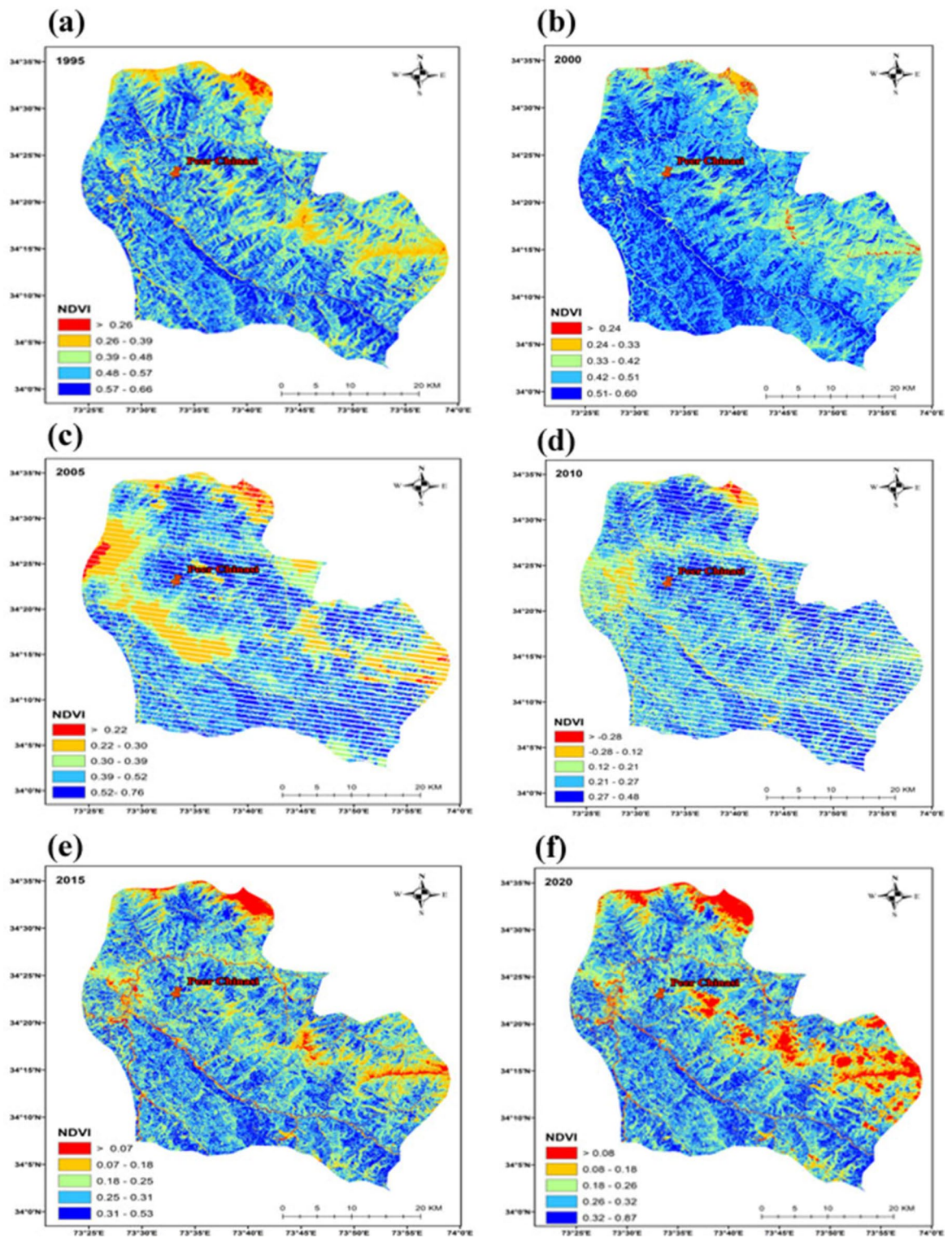


Fig. 2. shows the satellite-based NDVI variation temporally from 1995 to 2020.

[956,2825.08631358a,2608.57706282d,35y,0h,0t,0r/data=CigiJgokCXkkdsjBB0FAEWoFBBCW-EBAGZ7DNElhfFJAiah7yxvnaFJAoGgMKATA](https://doi.org/10.1038/s41598-024-71689-5)

Discussion

Numerous reports have been published relating NDVI to rainfall patterns. In a similar vein, by reference⁴¹ discovered that precipitation in Ethiopia's semi-arid areas was strongly correlated with NDVI levels throughout the growing season. According to the reference⁴², 80% of the Caatinga vegetation productivity anomaly may be

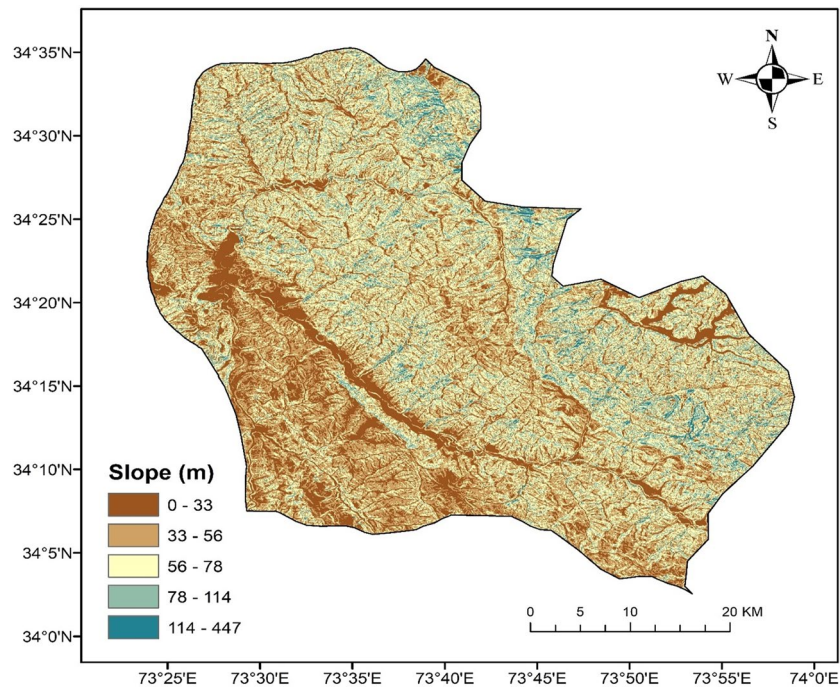


Fig. 3. Slope patterns of the study area.

accounted for by the rainfall anomaly using the vegetation index as a proxy taken by reference⁴³ in the Horn of Africa reported similar findings.

In China, a significant link between NDVI and precipitation was discovered by researchers^{17,44}. According to reference⁴⁵, NDVI across Northern Mongolia showed a positive association with yearly precipitation and a negative correlation with temperature¹⁶. Researchers^{13,46,47}, found that NDVI was more closely connected with rainfall than temperature on the Tibetan Plateau and the Loess Plateau, respectively.

In actuality, when evaluating vegetation response to climate change the perceptions of the residents can also be taken⁴⁸. In this study, the respondents perceived a major change in vegetation due to climate change and anthropogenic activities. A weak or negative (–) NDVI-Rainfall link implies that vegetation dynamics are influenced by the climate; a robust and positive (+) connection indicates changes in vegetation caused by humans. The researcher⁴⁹ also found comparable results in its worldwide survey.

According to researcher⁵⁰, precipitation is the key environmental element influencing NDVI changes in the Heihe River Basin, China. According to another researcher⁵¹, precipitation and land cover in Kenya's Mara River Basin revealed a highly positive association. According to reports, the primary human activities responsible for the deterioration of the local vegetation and the disappearance of the forest in this region include grazing, agriculture-related settlement growth, and wood collecting^{52,53}. According to researcher⁵¹, the highlands' growing pace of forest degradation is a sign of how much the high population density, 350inch/km^{22,24,39} value and exploit this forest on an economic, social, ethnological, and cultural level. It has been studied how some of the aforementioned factors relate to NDVI. The NDVI of the Wei and Jing River Basins, China, was shown to be primarily influenced by three variables: temperature, soil moisture, and precipitation. The researcher⁵⁴ demonstrated a tight link between the dynamics of grassland and temperature using NDVI-max at an annual time scale. Future studies could focus on exploring the connection between the environmental elements and the dynamics of the vegetation on the Pir Chinasi National Park.

Conclusions

The study described the dynamics of vegetation and how it responded to changing rainfall patterns and human pressures. It was proven that vegetation change dynamics and degradation are impacted by climate change as indicated by long-term rainfall anomaly (RAI). The study found that 10.81% of the area experienced substantial deterioration, while 23.57% experienced minor degradation. The total area of degraded lands was 34.38% suggesting a major change. To overcome these phenomena, steps of adaptation by the public–private sector are necessary. Improvement in plant cover was observed which is a positive sign. According to the NDVI-Rainfall relationships, the area was found to be significantly impacted by human pressures which require control by public–private partnership. The area under the influence of climatic variability and change is also large enough which requires immediate attention. Sustainable land management practices of conservation tillage, integrated pest management, and agroforestry help preserve soil health, water quality, and biodiversity while reducing erosion, pollution, and the degradation of natural resources. landscape restoration projects of reforestation, wetland restoration, soil erosion control, and the removal of invasive species are essential to achieve land degradation neutrality at the

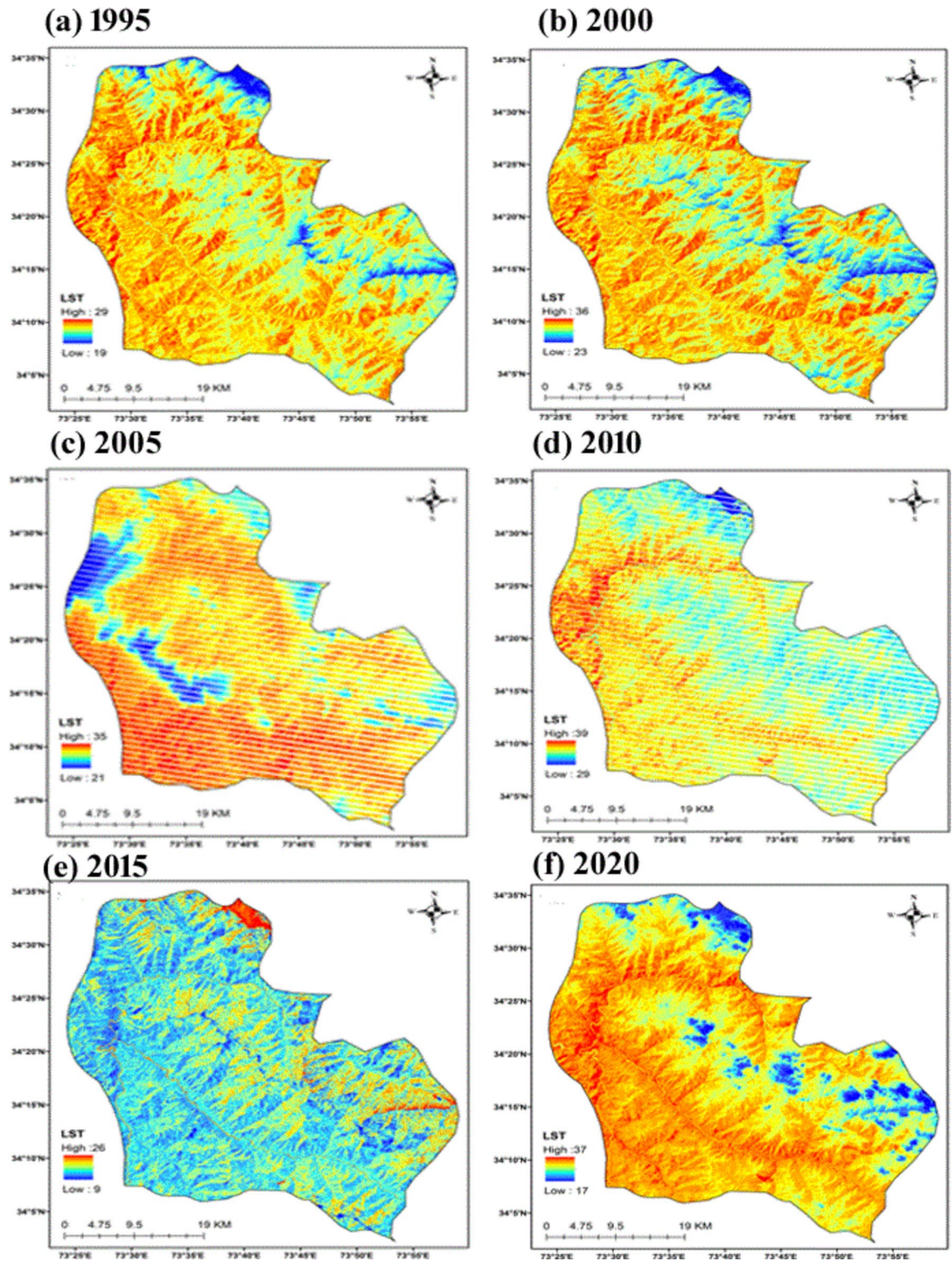


Fig. 4. Land Surface Temperature (LST) °C trends of the study area during the study period. The map was created using ArcGIS Desktop software (version 10.8.2, Esri Inc., Redlands, CA, USA). ArcGIS is widely used for creating slope maps from Digital Elevation Models (DEMs).

watershed scale. The quality and health of the vegetation were further harmed by unsustainable human activities such as agricultural development, overgrazing, settlement growth, and wood exploitation. However, climate change proved to be a driver of these phenomena. Even though these were the major causes, the degree to which the flora on the plateau tends to green up or brown out, could also be influenced by environmental variables such as soil moisture, solar radiation intensity and duration, drainage density, and topographic restrictions. This study does not conclude that the sole variables affecting vegetation dynamics are rainfall and human influences.

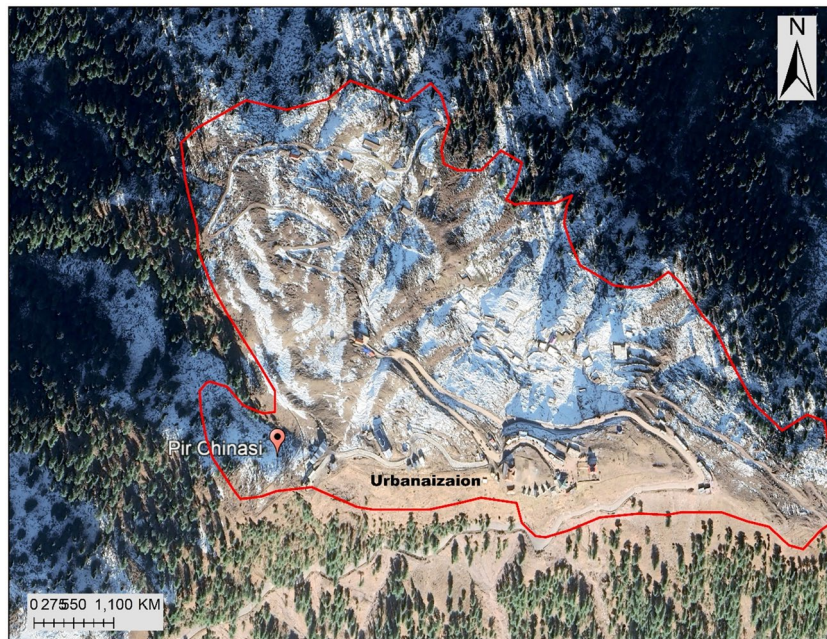


Fig. 5. Google Earth image of Pir Chinasi National Park.

In areas of the park where vegetation patterns indicate deterioration or loss of forest cover, afforestation, and replanting efforts could be done. These initiatives have the potential to improve ecosystem resilience to climate change, restore biodiversity, and sequester carbon. Implement sustainable land management techniques that boost agricultural production, and preserve and improve plant cover, such as conservation agriculture, rotational grazing, and agroforestry. These methods could lessen soil erosion, increase water retention, and protect the benefits provided by ecosystem services. In response to climate change and human intervention establish buffer zones, wildlife corridors, and protected areas to preserve important ecosystems and enhance landscape connectivity.

Data availability

Data is provided within the manuscript or supplementary information files.

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Competing interests

The authors declare no competing interests.

Research Ethics

Experimental research and field studies on plants (either cultivated or wild), including the collection of plant material, complied with relevant institutional, national, and international guidelines and legislation. Prior approval was undertaken from the Offices of Research, Innovation and Commercialization, National University of Modern Languages, Islamabad-Pakistan. We also took appropriate permission from the farm or field owner during specimens' collection and experimentation. We confirm that during the collection and execution of the experiment, the authors have complied with the IUCN Statement on Research Involving Species at Risk of Extinction and the Convention on the Trade in Endangered Species of Wild Fauna and Flora. All methods were performed in accordance with the relevant guidelines and regulations. All experimental protocols were approved by Offices of Research, Innovation and Commercialization, National University of Modern Languages, Islamabad-Pakistan.

Additional information

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