Analysis and Modeling of Temporal Forest Cover using Deep Learning Approach with Multi-spectral Remote Sensing Data and other Socio-Economic Drivers

Ayusha Tahir Abbasi

(2019-NUST-MS-GIS-319649)

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Remote Sensing and GIS

Institute of Geographical Information Systems
School of Civil and Environmental Engineering
National University of Sciences & Technology
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Author

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Thesis Supervisor:

Dr. Javed Iqbal

Thesis Supervisor's Signature: ______________________________

INSTITUTE OF GEOGRAPHIC INFORMATION SYSTEM

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

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Examination Committee Members

1. Name: Dr. Ejaz Hussain — Signature: ____________

2. Name: Dr. Abdul Waheed — Signature: ____________

Supervisor's Name: Dr. Javed Iqbal — Signature: ____________

Date: 24/01/23

Head of Department
Dr. Javed Iqbal
Professor & HOD IGIS, SCEE (NUST)
H-12, Islamabad

24/01/23
Date

COUNTERSINGED

Date: 03 AUG 2023

Dean/Principal
PROF DR MUHAMMAD IRFAN
Principal & Dean
SCEE, NUST

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Signature: ____________
Name of Supervisor: Dr Javed Iqbal
Date: 24/01/23

Signature (HOD): ____________
Date: 24/01/23

Dr. Javed Iqbal
Professor & HOD IGIS SCEE (NUST)
H-12 Islamabad

Signature (Dean/Principal): ____________
Date: 03 AUG 2023

PROF DR MUHAMMAD IRFAN
Principal & Dean
SCEE, NUST

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Table of Contents

LIST OF FIGURES		X
LIST OF TABLES		Xii
LIST OF ABBREVIATIONS		Xiii
ABSTRACT		xiv
CHAPTER 1: INTRODUCTION		1
1.1	Deforestation and Forest Degradation	2
1.1.2	Deforestation	2
1.1.3	Forest degradation	2
1.2	Deforestation in Pakistan	2
1.3	Role of advance technologies for deforestation assessment	7
1.4	Rationale and scope of the study	8
1.5	Objective	9
CHAPTER 2: MATERIALS AND METHODS		10
2.1	Study Area	10
2.2	Remote sensing data collection	14
2.2.1	Preprocessing	14
2.3	Image Classification	14
2.3.1	Sample collection	14
2.3.2	Artificial Neural Network Classification	14
2.3.3	Validation of classification	17
2.4	Estimation Socio-Economic Drivers	18
2.4.1	Collection of Socio-economic Data	18
2.4.2	Estimation of demographic behavior	18
2.5	Statistical Data Analysis	19
2.5.1	Multiple Regression Analysis	19
2.5.2	Stepwise Regression	19
2.5.3	Sawa Bayesian Information Criterion	21
2.5.4	Akaike Information Criterion	21
2.5.5	Adjusted R square	22
2.5.6	Variance Inflation Factor	22

CHAPTER 3: RESULTS AND DISCUSSION 24

3.1 Spatio-Temporal Landuse and Landcover Change in landcover 24

3.1.1 Accuracy Assessment of Landcover/Land use Change 24

3.2 Socioeconomic Survey 27

3.3 Deforestation Drivers 36

CHAPTER 4: CONCLUSIONS AND RECOMMENDATIONS 42

4.1 Conclusions 42

4.2 Recommendations 42

REFERENCES 44

APPENDICES 51

LIST OF FIGURES

Figure 2.1	Study Area map showing union councils, major roads, and water networks of district.	11
Figure 2.2	Methodology flow diagram.	12
Figure 3.1	Classified map year 1990 to 2000, b. Classified map of year 2000 to 2010, c Classified map of year 2010 to 2021.	25
Figure 3.2	a. Deforestation occurs from year 1990 to 2000, b. Deforestationoccur from year 2000 to 2010, c Deforestation occur from year 2010 to 2021.	26
Figure 3.3	Graph showing responses for people using LPG/Gas.	28
Figure 3.4	Graph showing responses for people since when they start using Gas/LPG.	28
Figure 3.5	Alternatives of fuel and their usage percentage in past years.	28
Figure 3.6	Responses for major activities causing deforestation.	31
Figure 3.7	Responses of people involved in agriculture.	31
Figure 3.8	Do you or people in your area have livestock?	31
Figure 3.9	Major sectors for the employed labor force.	34
Figure 3.10	Responses of people for road construction.	34
Figure 3.11	Responses of people having furniture business.	34
Figure 3.12	Responses to estimate infrastructure development.	35
Figure 3.13	Responses for impact of construction on deforestation.	35
Figure 3.14	Graph of Construction material used in Upper Dir.	35
Figure 3.15	Best criterion Value Graph.	44
Figure 3.16	Fit diagnostic graphs	44
Figure 3.17	Standardized coefficient of regression.	44

LIST OF TABLES

Table 1.1	Rate of deforestation in Pakistan from the Year 1995 to 2015.	6
Table1.2	Wood Consumption Sectors in Pakistan	6
Table 2.1	Types of datasets and software used in the research.	13
Table 3.1	Stepwise regression model selection summary.	38
Table 3.2	Analysis of variance for deforestation drivers.	38
Table 3.3	Criterion values for model selection.	39
Table 3.4	Parameter estimation of stepwise regression model.	39
Table 3.5	SAS result for proportion of variance among independent variables.	39
Table 3.6	Collinearity diagnostic of significant variables.	40
Table 3.7	Correlation coefficients of deforestation drivers.	40

LIST OF ABBREVIATIONS

Abbreviation	Explanation
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
BP	Back propagation
BIC	Sawa Bayesian Criterion
BTTAP	Billion Tree Tsunami Afforestation Program
CI	Condition Index
CP	Colin Lingwood Probability
FAO	Food and Agriculture Organization
GIS	Geographic Information System
GOP	Government of Pakistan
LC	Land Cover
LULC	Landuse Landcover
MLP	Multi-layer Precepetron
MSE	Mean Square Error
NN	Neural Network
POV	Proportion of Variance
SBC	Schwartz Bayesian Criterion
SOM	Self-organizing Mapping
SR	Stepwise Regression
TM	Thematic Mapper
UC	Union Council
VIF	Variance Inflation Criterion
WWF	World Wildlife Fund

ABSTRACT

Forest plays an important role in regulating carbon sequestration in the ecosystem. Monitoring temporal forest changes can identify management gaps that can be used for policymaking for afforestation initiatives. Many studies have been conducted to monitor the temporal change in forests. However, those studies used coarse spatial resolution data or lack social data to relate the causes of deforestation. This study uses high spatial resolution remote sensing data and socio-economic for temporal analysis of the upper Dir Forest area. The specific objectives of the study were to (1) analyze spatio-temporal long-term forest cover change using satellite data with neural network technique and (2) develop a spatial statistical model to analyze socio-economic drivers' interaction with forest in the region. Landsat imagery of the years 1990, 2000, 2010, and 2021 was classified using the Artificial Neural Networks (ANN) approach. For ANN classification, more than 400 signatures were collected for forest class and more than 300 signatures for bare land, agriculture, snow, and grass/shrubs. Areas of all classes were calculated and compared to estimate the change in forest cover. A socio-economic survey was conducted with the help of an online questionnaire to analyze the socio-economic situation of people. Statistical modeling was performed using linear regression model stepwise selection method in SAS software to determine most to least significant variable. The result shows the variation in the land cover classes during different study periods. Forest areas showed a decreasing trend from 1990 to2010. However, in 2021, there was an increase in forest cover due to afforestation. In contrast, agricultural areas increased by 1.37 percent, and built-up areas increased by 7.64 percent. However, bare land, and forest area decreasedby 9.1 and 4.17 percent from year 1990 to 2021 respectively. In general, in study district forestcover was 26% of the total area in 1990 and decreased to 20.18% in 2010, in 2021 due to afforestation, it became 21%, whereas agricultural area increased from 0.16% to 7.8% in 2021respectively. The study shows that most people earn their living by practicing agriculture. However, an increase in population caused an increase in food demand, leading to conversion of forest land in agriculture. The conversion of forest land into residential areas was also the cause of concern. Meanwhile, ineffective management, lack of coordination between government departments, and ignoranceof the forest department are major contributing factors in deforestation. The study recommend that we need to develop better energy alternatives and technically reliable inputs to decrease food demand, introduce awareness among organizations for coordination and introduce alternate earning sources for the local public of the district.

CHAPTER 1

INTRODUCTION

Forests help regulate the Earth's surface temperature and precipitation, safeguard soil nutrients, reduce flooding, and fix carbon. Woods are important for local populations andthe country's overall ecosystem, but the alarming deforestation rates raise the question of howlong these quickly disappearing forests can be sustained. According to Verburg, Kok, Pontius, and Veldkamp (2006), six million hectares of forest have been lost to agriculture, mining, tree cutting, encroachment, and forest fires worldwide. Humans altered the forest land cover to obtain food and other necessities. The global assessment indicated a 0.2 percent annual loss of forest area between 1990 and 2000, but forestprotection programs reduced deforestation to 0.13 percent between 2000 and 2005 (Keenan et al., 2015). Deforestation in the Himalayan mountains has a far-reaching impact on the ecosystemand economics of the nearby Indo-Gangetic Plain, causing disruptions in the hydrological cycle as well as repercussions such as soil erosion, siltation, floods, and desertification (Shehzad, Qamer, Murthy, Abbas, & Bhatta, 2014). InPakistan, firewood is the primary energy source for approximately 68 percent of the population.

The complex consequences of deforestation, which include both socioeconomic benefits and negative repercussions, there are growing socioeconomic concerns about the impactof deforestation, particularly in the twenty-first century. On the plus side, the loss of the world's forest resources has helped households fulfill their livelihoods and brought other socioeconomic, cultural, and spiritual benefits. It is recognized and relies on woods for survival, earning in part from the forests (Mayers and Vermeulen, 2002). InPakistan, firewood is the primary energy source for approximately 68 percent of the population.

Global warming, biodiversityloss, and soil degradation are long-term environmental effects and growing concerns exacerbated by increased deforestation (Mahapatra and Kant, 2005), and increasedpoverty in forest fringe communities. Deforestation is becoming a bigger problem for sustainable forest management, which focuses on combining environmental advantages with poor rural livelihood improvement to avoid deforestation (Goyena, 2019).

1.1 Deforestation and Forest Degradation

1.1.1 Deforestation

The deliberate clearance of forested terrain is known as deforestation. Forests have been razed throughout history and into modern times to make room for agriculture and animal grazing, and to obtain wood for fuel, manufacture, and construction. Deforestation can occur when forest area is converted to farmland, ranches, or urban usage. Deforestation has radically changed the world's landscapes.

1.1.2 Forest Degradation

When forest ecosystems lose their ability to deliver critical goods and services to humans and the environment, they are said to be degraded. Since the 1960s, more than half of theworld's tropical forests have been destroyed, and more than one hectare of tropical forest is destroyed or severely degraded every second. This state of emergency has had a significant impact on the rural population, which relies on wood for survival. This dependence, combined with changes in the ecosystem, has made them very vulnerable to future forest degradation - many households and workers in this region may lose their livelihood, skillset, and habitat.

1.2 Deforestation in Pakistan

Pakistan is the world's second most deforested country, with a yearly deforestation rate of 4.6 percent (Abbasi, Baloch, & Memon, 2011). Between 1990 and 2021, the Upper Dir district lost 4.17 percent of its forest area. Various deforestation hotspots, including Pakistan, which has Asia's second-highest deforestation rate (Gul, Khan, & Khair, 2014). Because of excessive logging and land clearing for agriculture and habitation, the world's forest cover areas are declining at an alarming rate (Hansen, 2013).

According to experts, forests should encompass at least 25% of the entire geographical area of a country, but Pakistan only has 5.7 percent of that.Only 16,440 km2 of Pakistan's total square kilometers area (881,913 km2) is covered by wood.Forests in Pakistan's alpine areas are fast degrading, particularly in the mountains, which is concerning and threatens the ecology. Pakistan lost 11.5 percent of its forest and woodland habitat between 2005 and 2015, according to the total rate of habitat conversion.

Pakistan had 4.2 million ha of forest cover in 1990, accounting for 4.8 percent of the total land area, with a loss rate of 0.7 percent per year from 1990 to 2000, according to government estimates (Shehzad et al., 2014). According to the FAO, from 2000 to 2010, the rate of decline was 2.0 percent per year (FAO, 2010). According to Global Forest Watch, Pakistan lost 69.2 hectares of forest cover in 2020, equating to 26.1 kt CO2 emissions. Deforestation is the degradation of forests caused by a process that reduces an area's natural forest vegetation and resources (Abere and Opara, 2012). Deforestation is the change of forest to permanent non-forested land use such as agriculture, grazing, or urban development (Chakravarty, Ghosh, Suresh, Dey, & Shukla, 2012).

Different forest types can be found inPakistan, with coniferous forests primarily found in KPK Northern Areas, Northern Punjab, Balochistan, and Azad Kashmir. The KPK forests are situated between 1,000 and 4,000 metersabove sea level. KPK districts like Dir, Malakand, Swat, and Mansehra, and Punjab districts like Rawalpindi have these forests (Sheikh & Wang, 2012).

Agriculture is a major contributor to deforestation. According to the United Nations Framework Convention on Climate Change, deforestation is mainly driven by cutting trees to expand agriculture (Tariq, Rashid, & Rashid, 2014). The high pace of deforestation is one of Pakistan's majorchallenges. According to many studies and assessments, Woods cover fewer than 4.6 million hectares of total land area. These forests are fast deteriorating, especially in hilly places, witha deforestation rate of approximately 1.5 percent, alarming and threatening ecosystems(Kamal, Yingjie, & Ali, 2019). Fuel wood accounts for around 53% of Pakistan's total yearly domestic energy.

Pakistanisone of the countries where forests are quickly degrading, with human activity being the primary cause. Table 1.1. shows the rate of loss in forest cover in Pakistan. Dependency on fuel wood is expected to remain high in the future because our economy needs to be stronger to shift away from conventional fuel. Population growth andfuel wood usage are expected to increase by 3% per year. The rising demand for household fuel wood diminish forests quickly (Benjaminsen and Ali, 2004). The rapid migration of people from rural to urban areas has resulted in a rise in settlement area due to the industrialization of cities that began with the industrial revolution.

Deforestation is accelerated by increased access to forests and markets via roads, waterways, and railroads. Forest fragments are more accessible than large, dense forests, while coastal and island forests are more accessible than others. Deforestation is slowing in all those forests 2 or 3 kilometers from roadways. Because the population is rising, more land isneeded for food, fuelwood, lumber, and other forest products (Angelsen and Kaimowitz, 1999). In the last 300 years, 7-11 million km2 of the forest has been cleared (Mawalagedara and Oglesby, 2012). According to the Forestry Sector Master Plan, wood consumption reached 29.5 million cubic meters (Mm3) in 1993.

Soil erosion and degradation are exacerbated by deforestation in Pakistan's northern provinces. (Tariq et al, 2014) also stated that as the rate of deforestation grew over time, land degradation and soil erosion in Dir Kohistan increased as well because albedo is more vulnerable to soil erosion and land degradation; forest and vegetation help to mitigate these negative effects. Deforestation in northern areas is due to ineffective practices and poor administration by the provincial forest agency. The department's forestry extension service is ineffective and does not address the underlying issues.

Illegal logging is a major cause of deforestation. The amount of wood consumed, and the overall amount of wood collected from Pakistan's State forests are used to determine the amount of illegally harvested wood. Illegally collected timber was four times more valuable than legitimately harvested wood. Illegal logging is a significant part of the underground economy (Cashore et al., 2016). Pakistan had a 7% green cover when it gained independence in 1947, but afterBangladesh's independence in 1971, it was reduced to fewer than 5%. As of 2015, Pakistan's forest cover (percentage of land cover) was 1.91, according to the World Bank. Over the last 25 years, Pakistan's forest cover has decreased from 3.28 percent in 1990 to 1.91 percent in 2015. Pakistan is at a critical juncture because only 2-5 percent of its forest cover remains (Kurosaki, 2008). Pakistan now produces approximately 14 million cubic meters of wood, which is expected to increase to 32.6 million cubic meters by 2016. To meet people's demands, 33 million cubic meters of wood will be required by 2016. Between 2003 and 2013, the usage of (building, furniture, village carpentry, mining timber, and industrial fuelwood) increased by 42%, from 3123000 m3 to 4434000 m3, as shown in Table 1.2.

According to the conceptual framework, the direct causes of deforestation are an expansion of infrastructure and agriculture, extraction of wood, and other factors, including pre-disposing biophysical conditions and social trigger events (Geist and Lambin, 2001). This framework was used in a global study on the evolution of drivers of deforestationand their potential impacts on the cost of schemes for avoiding deforestation (Shehzad et al., 2014).

Forests in Kashmir and Khyber Pakhtunkhwa are vulnerable to militant organizations cutting timber illegally. Between Pakistan and Afghanistan, illegal timber is smuggled. Smuggled timber from Pakistan is then returned to Pakistan under the guise of duty-free Afghan timber. After being smuggled into Pakistan, the timber is shipped to Karachi and then to the Gulf States (Nizami, 2013).

Government agencies must battle illicit logging to protect the woods. However, all logging, whether illicit or legal, results in deforestation. The government has implemented tree-cutting bans in recent policies (1991, 2005, and 2010). Nonetheless, corruption, political meddling, a lack of genuine commitment, and thievery on the part of the government to bring the offenders to justice have not stopped the wood mafia from harvesting forests. As a result, timber traffickers employ all methods to smuggle wood for short-term financial gain.

Due to current regulations and government attention, only 20 timber licenses were awarded, covering a forest area of 910 thousand hectares. The number of active wood licenses has decreased by 79 percent due to the government's recent rigorous forest protection regulations. To address market demands, the government encourages the private sector to invest in industrial forest plantations, which has resulted in 172 industrialforest plantations in the last decade. As a result, Industrial Forest Plantations and Timber License Agreement holders were responsible for almost 53% of overall timber production.

Deforestation occurs by natural phenomena like flooding, drought and tsunami but in the Upper Dir district, the major reason is socio-economic factors. People of district don’t have enough opportunities to learn skills other than construction and agriculture. Half or may be more than half of the population are involved in agriculture. The ratio of teacher to schools is very low so people are not able to learn more skills. There is an immediate need to save our natural resources as they are declining at an alarming rate for this purpose, we must change our behavior our environment will be saved if we want it to be safe and the government must educatepeople about that and make incentive policies in the forest sector.

Table 1.1. Rate of deforestation in Pakistan from the year 1995 to 2005.

Variable	1995 - 2000	2000 - 2005	2005 - 2010	2010 - 2015
Total forest area in the base year (ha)	2321000	2116000	1902000	1687000
Annual forest loss (ha)	41100	42800	43000	42800
The annual rate of deforestation %	1.63	2.02	2.26	2.54

Table 1.2. Wood consumption sectors in Pakistan.

Consumption (Km3)	1995 - 2000	2000 - 2005	2005 - 2010	2010 - 2015
Construction	1711	2381	3322	3930
Furniture	2216	3123	4434	5310
Village Carpentry	62.7%	57.4%	55.5%	53.4%
Mining Timber	505	742	1112	1380
Industrial Fuelwood	1320	2319	3551	4633

1.3 Role of Advance Technologies for Deforestation Assessment

Geographical Information System, Remote sensing and artificial neural networks has been efficiently and widely used much in single thematic analysis such as land use and land cover change mapping (Lambing, 1997) (Rogan et al., 2002), forest monitoring (FAO, 2000), watershed management and forest fire management, and forest strategy appraisal (Nagendra et all., 2005). Remote sensing studies showed that the rate of deforestation in Kpk is high and within 30 years forest will completely disappear. ANN were extremely useful in assessing forest cover change and investigating socioeconomic drivers of deforestation. Non-parametric ANN approaches offer a particular advantage over statistical classification methods in that they do not require a priori knowledge of the distribution model of input data (Lee et al., 2020).

Remote sensing change detection analysis, in particular, can be used to identify regions of rapid change to focus management efforts (Rogan and Roberts 2002; Kennedy 2009;Henders and Ostwald 2012). Repeated satellite photos are important for visualizing natural resource dynamics at a certain time and location, and quantitatively assessing land coverchanges (Tekle, 2000). Satellite remote sensing helped us collect images of same the season at different times as these landcover changes are classified on same season images of different times.

These activities have provided vital theoretical insight into how the forest in the region influences these features. These advanced technologies will aid in the resolution of numerous issues that a rapidly growing population faces, including the provision of facilities to improve their economic standards of living, the lack of alternative energy sources, a lack of earning resources, insecure housing tenure, and a lack of coordination and communication between government levels. The result is a recognition that new studies and planning can do a lot to reduce natural resource loss.

GIS and remote sensing are two key technologies that can be utilized to combine spatial analyses with machine learning algorithms to forecast deforestation. Geographic studies encompass a wide range of spatial issues at various scales (Gharani, Suffoletto, Chung, & Karimi, 2017).

1.4 Rationale and Scope of the Study

This study helps us find how people's social and economic activities cause deforestation, what those activities are, and how people depend on forests for their living. Because of the diverse effects of deforestation, including both socioeconomic benefits and negative consequences, there is growing socioeconomic worry about its influence, particularly in this century. On the plus side, the dwindling of the world's forest resources has helped to secure household livelihoods and brought additional socioeconomic, cultural, and spiritual benefits. Nearly 500 million to 1.6 billion people are estimated to live in and rely on forests, with the forests providing a portion of their income. UC-wise socio-economic survey data and reports, forest coveranalysis and socio-economic factors that on forest cover were formerly estimated on forest cover for the Upper Dir district of KPK, Pakistan. The study was carried out by monitoringand collecting data on population living standards, amenities available to them, how much of the population depends on agriculture, what are the key employment sectors, and how much energy and building resources are available.

Increased forest cover loss and quickly dwindling resources warn us of the growing likelihood that Pakistan may experience increased economic pressure in the future, especially as its population continues to grow and promote urbanization. Most of the houses in Upper Dir have timber roofs; if this infrastructure continues, natural resources will continue to deplete. Most of the people are involved in agricultural activities, turning land into agricultural land, which has increased in recent years while forest land has decreased (GoP, 2016). People are generally unaware of technologies, and there is a lack of planning and management. In 2016 and 2017, numerous trees were planted to conserve forests through afforestation, a significant initiative to safeguard land from deforestation (BTTAP, 2016).

More than 1 billion people live in or near forests, which they rely on for fuel, food, medicine, and building materials. We all need wood in our daily lives, worldwide demand for timber products is expected to triple in the next three decades. However, because human activities have already resulted in the loss of roughly 40% of the world's forests, forest conversion is being monitored by estimating deforested area and factors that substantially impact deforestation using current technologies. (PBS, 2013).

This research integrates advanced remote sensing and GIS methodologies and technologies that are fast, reliable, and timesaving, as well as ANN and statistical models for more dependable outcomes. This research also gives decision-makers useful information on expanding the forest area and providing better alternatives for various activities such as construction and earning resources. Moreover, how government sectors handle LULC by keeping their borders. Unfortunately, public awareness is poor; nonetheless, this study gives people useful information on how to obtain better work and energy sources, improving their living level .

Because of limited economic resources and severe poverty, a major portion of the Upper Dir population relies on non-timber forest products for a living, andcontinued destruction would exacerbate their plight. Improved conservation activities are needed to stop deforestation in Upper Dir, such as expanding livelihood possibilities, providingalternative energy sources, and strengthening management methods (Shehzad et al., 2014).

The regression strategy utilized in this project is stepwise regression to estimate the drivers of deforestation. Stepwise regression is the iterative creation of a regression model in which the independent variables to be utilized in the final model are chosen step by step. It entails incrementally adding or eliminating potential explanatory factors, with each iteration requiring statistical significance assessment. The basic purpose of stepwise regression is to uncover a collection of independent variables that significantly influence the dependentvariable using a series of tests such as F-tests and t-tests.

1.5 Objectives

The objectives of the study were to:

- Analyze Spatio-Temporal Long-Term Forest Cover using Satellite Data with Neural Network Technique.
- Develop a Spatial Statistical Model to Analyze Socio-economic Drivers' Interaction with Forests in the Region.

CHAPTER 2

MATERIALS AND METHODS

2.1 Study Area

The higher half of the former District Dir is known as Upper Dir. Dir was a state ruled by Nawab Shah Jehan Khan at the time of independence. It is located in 35.3356N and 72.0468E.Upper Dir District is 3,699 sqkm in the area from which 3.98% is an urban area and 96.02% is rural area with a population size of 946,421 which comprises 49% (approx.) male and 51% female population. Among crops of Upper Dir, wheat holds central importance and is indeed the largest produced crop of the district. In 1969, it was amalgamated with Pakistan, and in 1970, it was designated as a district. It wasdivided into Upper and Lower Dir districts in 1996. This district is located in Pakistan's northwestern region. Chitral district and Afghanistan border it on the north and northwest, Swatdistrict on the east, and Lower Dir district on the south. The district is divided into Dir and Wari subdivisions for administrative purposes and five tehsils: Dir, Barawal, Kalkot, Wari, andKhal. There are 28 UCs, all of which are in rural areas. It is one of KP's newest districts, established in 1996. It is primarily a mountainous region with little development in terms of infrastructure. Agriculture, horticulture,minerals, tourism, and remittances from abroad are the population's primary sources of income.

Upper District is so well with forested land, locals currently use it primarily for firewood. It has a variety of forest types, including sub-alpine, dry, moist, oak, sub-tropical chir pine, and sub-tropical broad leafed. Deodar, Kail, Fir, Spruce, and Chir are prominent forest trees, but Oak is a particularly prominent broadleaf species. In the neighborhood, some small-scale manufacturing operations produce high-quality furniture. This industry has the potential to flourish if properly managed and motivated. Furthermore, because countries have far exceeded their carbonemission quotas, they can earn some "carbon credits" with the remaining forest.

Currently, regional growth should focus on the primary sectors. Upper Dir District has 1170 tons of high-quality granite deposits and 5875 tonnes of Feldspar reserves. However, according to the Directorate of Mines and Minerals report,there are also Aquamarine and Copper reserves in the Dir district, although more investigationand research are needed to establish specific values.

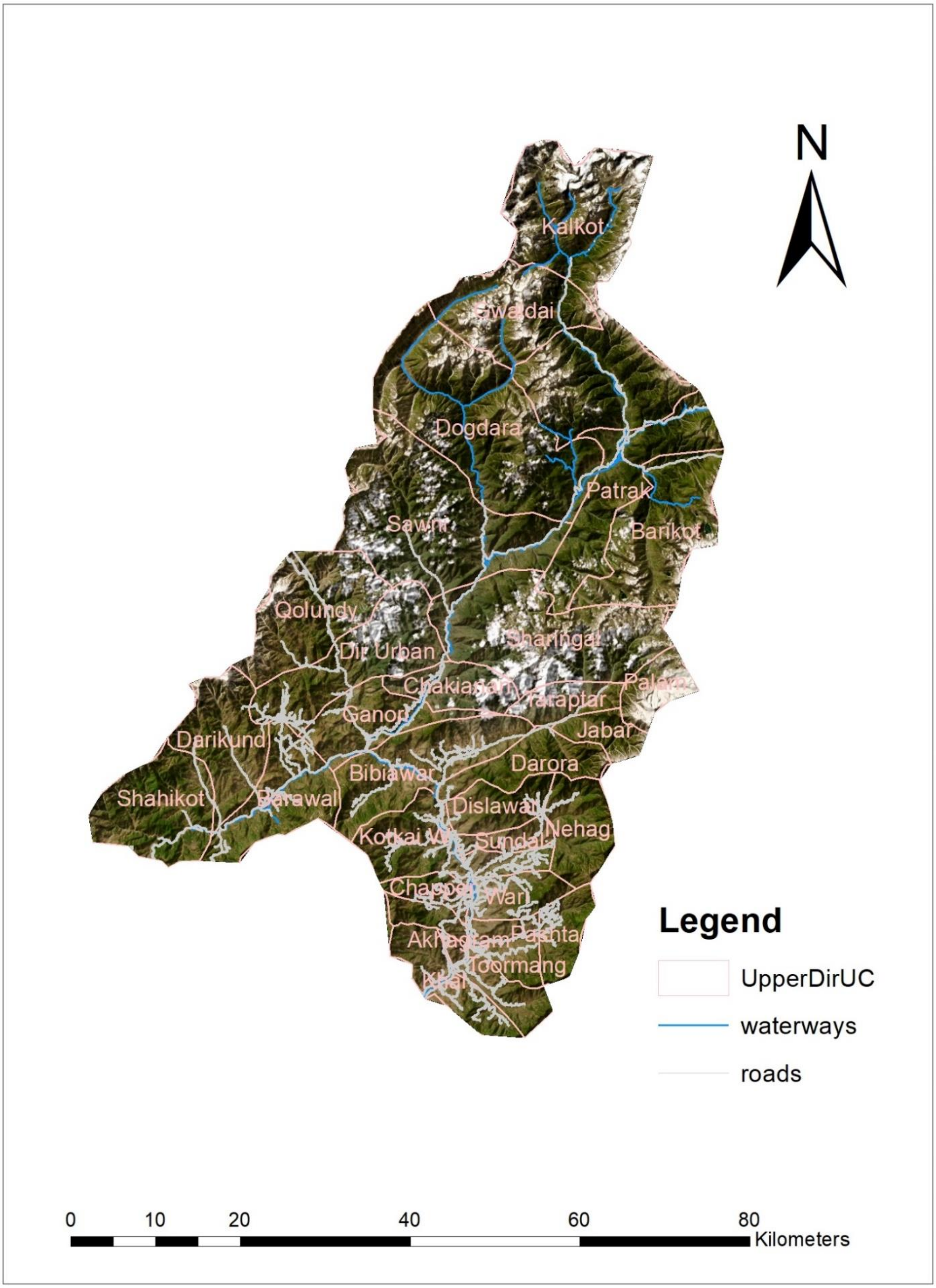


Figure 2.1. Study area map showing union councils, major roads, and water networks of district.

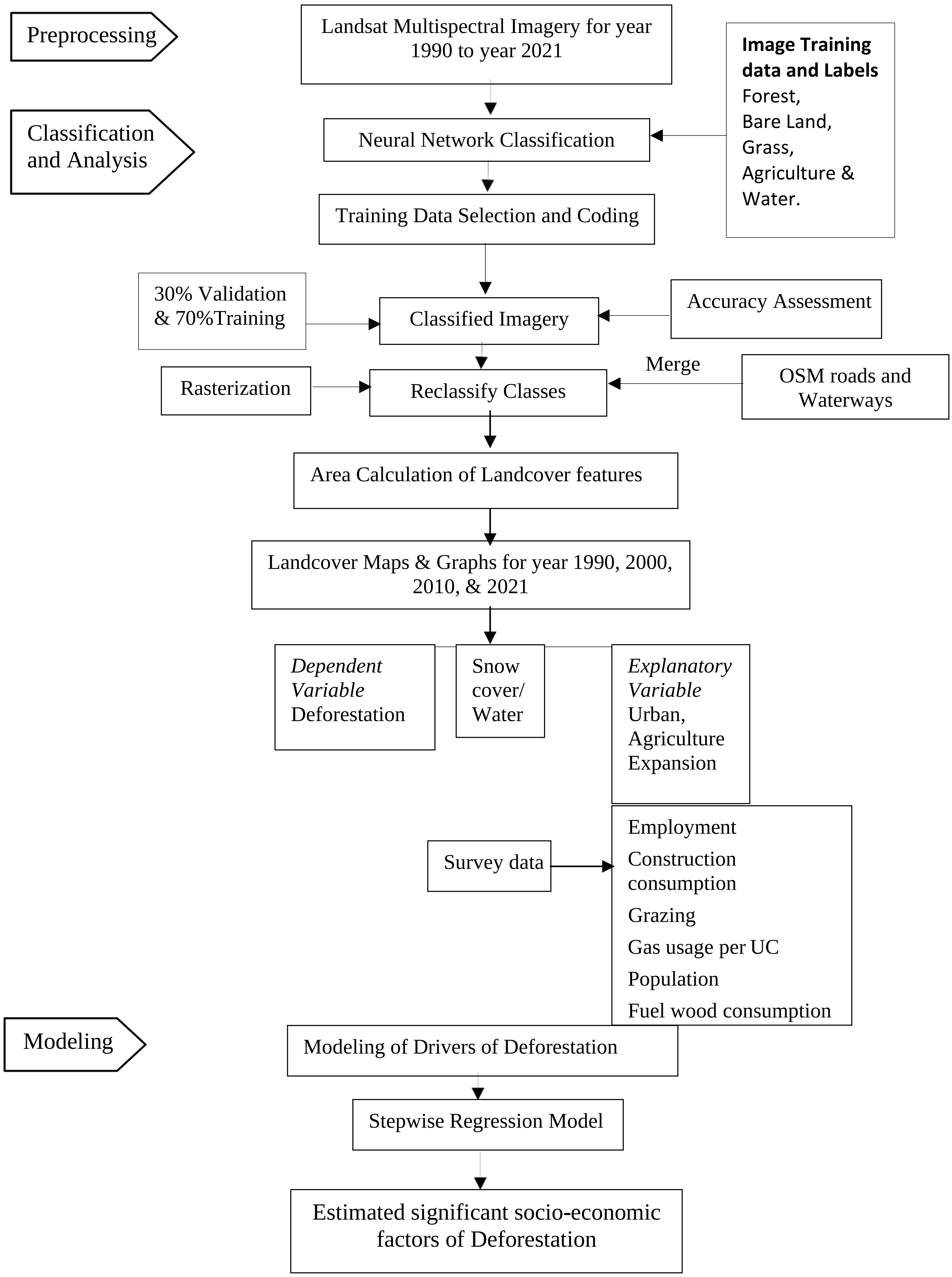


Figure 2.2. Methodology flow diagram.

Table 2.1. Types of datasets and software used in the research.

Raster Data	**Description**	**Source**
Satellite Imagery	Images of years 1990,2000, 2010, 2021 of same season. Landsat 5, 7 and 8 downloaded.	USGS/ European space Agency
Agriculture	Information will be collected from land cover classification; how much forest area is converted into agriculture.	Extracted from Satellite image classification
Bare land Expansion	Information will be collected from land cover classification; how much forest area is converted into Bare land.	Extracted from Satellite image classification
Roads, water ways shapefiles	Shapefile	Open street Map OSM
Urban area	Polygon created on built-up areas	Google Earth pro
Population	UC wise population data downloaded	Pakistan bureau of statistics PLSM 2015
Training sample	Training samples of classes built-up urban features, water bodies, forest and agriculture will be collected these samples will use in training the algorithm and validation process.	Google Earth Pro
Fuel wood consumption. Agricultural activities. Grazing. Literacy Rate. Consumption of wood in various sectors. Major employment Sectors. Living standards	Survey conducted to estimate area where more people are involved in agriculture and grazing. And where people are still not using gas cylinder for cooking and other purpose. And those area where people work depends on wood.	Survey, PSLM 2014-15 PSLM 2019-20
Software Required	ENVI ERDADS IMAGINE SAS for Academia ARCGIS Version 10.4.1	

2.2 Remote sensing data collection

Landsat 5, Landsat7 and Landsat8 imagery were downloaded for years 1990, 2000, 2010, and 2021 for forest-cover change analysis. To reduce chance of miss-classification, all images are of same season September/October.

2.2.1 Preprocessing

Atmospheric correction and radiometric correction have been performed using ENVI. Tiles were color corrected and then mosaiced in ArcMap software then the study area was extracted by shapefile.

2.3 Image Classification

2.3.1 Sample collection

More than 500 samples were taken for each class including bare land, forest, agriculture, snow, and grass/shrubs for classification. 70% of samples were used for training and 30% for validation. These samples were collected from satellite imagery in the form of polygons.

2.3.2 Artificial Neural Networks Classification

This model employs ground sample points for classification, with 70% of points used for training and 30% for validation of classified data. Artificial Neural Networks wereemployed to examine deforestation trends over the last three decades. ENVI was utilized, whichhas a built-in tool for NN classification. Our automated ANN classification system comprised our supervised Multi-Layer Perceptron (MLP) network module and a single unsupervised Kohonen's Self-Organizing Mapping (SOM) neural network module. However, ENVI offers supervised categorization. ANNs were created to emulate the brain's neural storage and analytical functions as pattern identification and data analysis tools.(Singh et al., 2017)

Non-parametric ANN approaches offer a particular advantage over statistical classification methods in that they do not require a priori knowledge of the distribution model of input data. Previous studies of deforested areas based on remote sensing data and deep learning have also shown a high accuracy rate of (~90%), likely because the land cover is divided into only two or three classes (de Bem, de Carvalho, Guimarães, & Gomes, 2020). The MLP neural network is the most used model for image classificationin remote sensing. It is a supervised model that uses single or multilayer perceptrons to mimicthe underlying input-output correlations. MLP networks typically have one input layer, one ormore hidden layers, and one output layer and are trained using the supervised backpropagation(BP) technique.

It loads training data into a satellite image and uses 70% for training and30% for validation. After encoding the training data, we trained the network using 100 iterations and a tolerance of 0.2. After 100 iterations, processing ceased and generalization happened, and unclassified pixels were turned into a classified map. It exhibits improved mapquality in terms of accuracy. Still, some portions of the 2021 image have cloud cover that will be manually identified by observing which feature class is behind it. Because certain forest trees appear darker due to shadow due to slope and elevation, many samples were obtained fortraining so that the model could accurately predict the forest class. However, for some classes,over-prediction occurs when one has more training data than the others, and the same is true for under-prediction. For each class, NN can work with actual samples. For better results, it necessitates meticulous sampling of feature classes; the output is dependent primarily on sampling. In terms of accuracy, it outperforms traditional methods.

An input vector is placed on the input nodes of MLP, propagating to the output layer via the weight connections and hidden layer. For each vector in the training set, this is done. Each node in the hidden and output layers uses an activation function to alter the sum of its inputs.

$$Z = \iota j \;.\; \omega j \iota * o \iota \text{.........Eq.1}$$

In equation 1, o is the remotely sensed and GI~ input data being presented to a node ι and multiplied by a weight ω. The products are summed at the hidden nodes to produce a value Z, for the *j*th layer, and the calculated output nodes are compared with the target values. Values of the output nodes are calculated based on GIS and remotely sensed data values input to the neural net; if, it does not match with targeted values, it’s an error. Classification is performed in ENVI using the NN tool for the years 1990, 2000, 2010 and 2021.Five LC classes were extracted from images: forest, grass, bare land, agriculture, and water. Urban features were collected from google earth pro in the form of a shapefile and then mergedinto images. Similarly, the roads network and water ways are downloaded from open street map and merged intoextracted classes.

To assist in developing responsible forestry policies, this project aims to use ANN to create a basic statistical model that can predict deforestation drivers and estimate forestcover loss. ANN is a type of computer software and hardware that mimics biological neural network computing system information processing models with the ability to train, and it is highly convenient and can produce results rapidly after learning is completed (Bayindir, Colak, Sagiroglu, & Kahraman, 2012).

Many specialists have noticed that the BP neural network alone does not substantially improve remote sensing picture classification. As a result, they shifted their research focus to improve the NN algorithm's structure and chose more scientific parameters through various approaches to increase the classification accuracy of remote sensing photos. The classification accuracy of a multilayer forward feed neural network used to classify land cover types was good (Atkinson & Lewis, 2000).

A study demonstrated that artificial neural networks could successfully tackle the misclassification problem that traditional classification methods have. The image's spectral characteristics are combined with the culture's textural traits, resulting in a considerable increase in classification accuracy (D. M. Miller, 2000).

When employing Landsat TM data, a study found that NN could map general land-cover classes like water, land, forest, and urban with more accuracy than a conventional maximum-likelihood classifier (Hepner, Logan, Ritter, & Bryant, 1990). They discovered that the neural-networkalgorithm performed better when mapping broad land-cover classes using the same approach (Fitzgerald & Lees, 1994). To map linear geological features, Landsat TM images was used. The NN was superior to linear discriminant functions and k-nearest neighbors for this purpose when trained using digitized lineament maps (Skidmore, Turner, Brinkhof, & Knowles, 1997).

The pixel-level classification of complicated geographic datasets is a demanding issue, made harder by increasing the volume and variety of satellite-acquired data. Automated supervised classifiers based on statistical and machine-learning methodologies are frequently used to generate a discrete choropleth map in which each pixel is assigned a class label (Skidmore et al., 1997).

The function of a classifier can be expressed as mapping its input variables to its (predetermined) output conditions. We can compose

$$\Re^{p} \quad \Pi\ '(n, p) \longrightarrow \Pi^{q} \text{......................} \text{Eq.2}$$

where p is the number of attributes, q is the number of classes and n is the number of samples. The goal of classification is to select an output class from a different phenomenological domain. Π, the classification scheme, to that of the input attributes ($\Re$) for each input vector $\boldsymbol{x}^{p}$. Unsupervised and supervised classifiers are two types of transformation models. In the case of supervised classification, the user chooses the scheme Π and the classifier learns an approximation Γ '(n, p) to the required transfer function Γ (n, p). This is done by looking at the training set of data for which the right classification has already been identified; as a result, the common scheme of ground cover type is frequently obtained from anattribute domain that may include numerous bands of LANDSAT data as well as supplementary data. Unsupervised Self-organizing Mapping SOM and I Supervised MultilayerPerceptron MLP are two classification modules in NN.

The MLP neural network is the most often used network model for image classification in remote sensing. A supervised model uses single or multilayer perceptrons to mimic the underlying input-output correlations (Kanellopoulos & Wilkinson, 1997). MLP networks typically have one input layer, one or more hidden layers, and one output layer, and are trained using the supervised backpropagation (BP) technique. The generalized delta rule used to update the weights in the standard BP algorithm is typically slow and unreliable (Yuan et al., 2009).Many operational factors, such as the size and quality of the training data set, network architecture, training parameters, and over-fitting difficulties, affect MLPs. These aspects are application-specific and should be addressed on an individual basis.

After classification, there must be a need to know how much urbanization and development have occurred as upper Dir is mostly rural. Roads, and shapefile was downloaded from open street map OSM then all classes converted into vector shapefile and the roads network was merged into the shapefile. Then shapefile is converted into raster and reclassified into map.

2.3.3 Validation of Classification

Samples were collected from google earth for accuracy assessment; almost 400 – 600 samples were collected for each class to calculate accuracy by dividing reference values to the actual values of classes. The agreement between the observed and anticipated values is also measured using kappa coefficients.

2.4 Estimation of Socio-economic Drivers

2.4.1 Collection of Socio-Economic Data

To find change in landcovers, the most significant factors behind loss in forest cover were collected through a socio-economic survey. All the socio-economic factors of deforestation i.e., Population growth, fuel wood consumption, employment sectors, resource availability, wood consumption for construction, agriculture growth, animal grazing all these factors were collected through online questionnaire. This study illustrates the socio-economic factors behind deforestation (Mccray, 2017). A survey questionnaire was created online for data collection. This questionnaire is distributed all over the Upper Dir district. At least three responses were taken from each UC. Most of the responses are from Dir urban and Wari. Then all these responses were converted into percentages, fields of each survey question were added to UC shapefile with response percentages all the landcover class data were also extracted from raster to UC shapefile into their labeled field. This UC shapefile is converted into an excel sheet uploaded to SAS software for regression analysis. All the sources of dataset used in methodology are enlist in Table 2.1.

2.4.2 Estimation of Demographic Behavior

Because of the constantly growing population, LC has undergone modifications to meet the needs of people trying to make a living. Approximately 4% of the population lives in cities, while 96% lives in rural areas. Due to the scarcity of resources in rural areas, they rely heavily on natural resources to earn a living, food, and other necessities. The population growth ratein the Upper Dir district is 2.7, and the population for 2021 has been determined using this rate.As the world's population grows, so does the demand for food and resources, which substantially impacts the area of land-cover features.

Although the fundamental drivers of deforestation are well understood, it is difficult to estimate their contribution to deforestation, and there is no clear understanding of how these factors interact. Land cover and land-use change simulations are important in natural resource management and academic research. Several useful aspects contribute to the creation of models in deforestation (Ahmadi, 2018).

Studying driving forces is more problematic; there is no single method, but the roots of the different methods are the same (Shehzad et al., 2014). There are various models available eachwith specific advantages and disadvantages.

2.5 Statistical Data Analysis

2.5.1 Multiple Regression Analysis

Regression can assist in understanding the variables behind observed patterns by allowing you to model, analyze, and explore correlations. In this project, regression analysisis performed to understand the significance of socio-economic factors on deforestation, a dependent variable extracted from classified imagery and then converted into points. Then average deforestation for and fire-wood consumption, grazing, gas usage, agriculture, urbanization, furniture market, population growth, construction of roads, and construction buildings are explanatory variables. We use the stepwise regression model it performs better for data with multicollinearity. All socio-economic variables are correlated with each other to some extent. As we know as urbanization increases, construction also increases. The construction variables of roads and buildings are derived from people's responses whether construction occurs in their UC or not. Fire-wood consumption and gas usage were also derived through survey responses. Grazing is derived through responses to question about livestock. The district's population is from PBS and PLSM and for the year 2021 is calculated through the growth rate.

2.5.2 Stepwise Regression

Stepwise regression has been performed using SAS software and can be accomplished in one of two ways: by testing one independent variable at a time and including it in the regression model if it is statistically significant, or by including all possible independent variables in the model and eliminating those that are not statistically significant. When dealing with several independent variables, this type of regression is used. The selection of independent variables is made using an automatic procedure that does not require human interaction in this technique. This task identifies relevant variables using statistical values such as R-square, t-stats, and the AIC measure. Stepwise regression is a method of fitting a regression model by adding or removing co-variates one by one according to a set of criteria. This modeling technique maximizes prediction power while using the fewest number ofpredictor variables possible. It is one of the strategies for dealing with data sets with increaseddimensionality. Because some people combine the two methods, there are three approaches to stepwise regression. Forward selection starts with no variables in the model, tests each one as it is introduced, and keeps the statistically significant ones, repeating the procedure until the results are perfect.

Stepwise regression is the iterative creation of a regression model in which the independent variables to be utilized in the final model are chosen step by step. It entails incrementally adding or eliminating potential explanatory factors, with each iteration requiring statistical significance assessment.

Backward elimination begins with a collection of independent variables, then deletes one at a time, checking for the statistical significance of the eliminated variable. The standard stepwise method combines the first two procedures to determine which variables should be included and which should be eliminated.

Training and testing data were divided at random. Two-thirds of the sites were designated, the remaining one-third were designated as training sites, and the remaining one-third were designated validation sites. The models were validated to generate a Mean Square Error (MSE) value by predicting outcomes for the validation dataset and comparing them to the observed data. For SR models, modified R2 was used to determine fit. Modeling was performed using SAS for the Academicssoftware package. It has several linear models, shown below.

In this research, we use stepwise linear regression, xlsx file is created for all dependent and independent variables UC-wise i.e., it shows values of all variables per UC. *Avg_Deforestation* column is added as the dependent variable. Whereas *furniture, construction_per, fire_wood, grazing, gas_per, Avg_roadDistance, Avg_Urbandistance, Avg_Agriculture* & *Population_2021* are added as continuous variable (Liu et al., 2022).

In Model Effect Function add single effect. Which has 3 options Add, Cross, Nested. Add option is used which allows only main effect to the model of a variable. Cross adds two or more variable effect and nested create hierarchically nested models. The confidence level is 95% and all residual and diagnostic plots are checked. The model is set to add and remove effects according to the significance level, default. The default significance level is 0.15. Criteria for adding and removing effects is Sawa Bayesian Criterionand AIC. The model's goodness of fit is set to Adjusted R square.

2.5.3 Sawa Bayesian Information Criterion

A Bayesian variation of the AIC criterion was used to create this model selection criterion. The number of observations n, the SSE, the pure error variance fitting the entire model, and the number of independent variables, including the intercept, determine the Sawa Bayesian Information Criterion (BIC).

All residual and diagnostic plots are examined, and the confidence level is 95%. The model is set to add and delete effects based on the preset significance level. The default level of significance is 0.15. Sawa Bayesian Criterion and AIC are two criteria for adding and eliminating effects. Adjusted R square is the model's fit quality.

In general, models with a lower BIC are recommended. It is connected to the Akaike information criteria and is based on the likelihood function (AIC). Adding parameters to models can increase its likelihood, leading to overfitting. By including a penalty term for the number of parameters in the model, the BIC solves this problem. In comparison to AIC, the penalty term in BIC is longer.

It is either independent of the prior or constant. It can determine how well the parameterized model is at predicting data. It penalizes the model's complexity, definedas the number of parameters in the model. It is like the minimal description length criterion but with a negative sign and can be used to determine the number of clusters based onthe inherent complexity of a dataset. Other penalized likelihood criteria, such as the RIC and the Akaike information criterion, are closely connected.

2.5.4 Akaike Information Criterion

Hirotugu Akaike, a Japanese statistician, created the Akaike information criterion (AIC). It is a statistical metric that is used to compare time series models. However, because the AIC isn't based on a hypothesis test, it can't guarantee a model's quality compared to other models. Thus, if all of the models under consideration fit badly concerning a given set of data or observations, the AIC will identify the model that fits the data or observations a little bit better than the others.

AIC is most commonly used in statistics for model selection. You can determine the best fit for the data by calculating and comparing the AIC scores of various models. When testing a hypothesis, you may collect data on factors you are unsure about, especially if you are

experimenting with a novel concept. You want to determine which of yourindependent variables accounts for the variation in your dependent variables.
Lower AIC values are preferable because AIC penalizes models with additionalparameters. When two models explain the same amount of variation, the one with fewer parameters has a lower AIC score and is the better-fit model.

2.5.5 Adjusted R square

Adjusted R-squared is a variant of R-squared that considers the number of predictors in the model. When the new term improves the model more than would beanticipated by chance, the adjusted R-squared increases. When a predictor improves the model by less than expected, it declines. The corrected R-squared is usually positive, not negative. It is never greater than R-squared. When you add additional independent variables or predictors to a regression model, theR-squared value rises, tempting the model's creators to add even more variables. This referred to as overfitting, might result in an unjustifiably high R-squared score. The adjusted R- squared method is used to determine how reliable a connection is and how much independent variables influence it.

The most evident distinction between adjusted R-squared and R-squared is that adjusted R-squared considers and tests many independent factors against the stock index, whereas R-squared does not. As a result, many financial professionals prefer to utilize modifiedR-squared since it may be more accurate. Additionally, investors can learn more about what isaffecting a stock using the adjusted R-squared model, on the other hand, it has several drawbacks. One of the most important limitations of this approach is that R-squared cannot be used to identify whether coefficient estimates and forecasts are skewed. Furthermore, the R-squared cannot tell us which regression variable is more relevant than the other in multiple linear regression.

2.5.6 Variance Inflation Factor

The variance inflation factor (VIF) is a metric for determining a multicollinear set of multivariate regression variables. The VIF for a regression model variable is equal to the ratio of the total model variance to the variance of a model that only includes that single independent variable in mathematics. For each independent variable, this ratio is determined. A high VIF suggests that the independent variable linked with it is significantly collinear with the other variables in the model.

Because the inputs all influence each other, multicollinearity is a challenge in multiple regression. As a result, they are not truly independent, making it difficult to determine how much the interaction of the independent variables influences the dependent variable, or outcome, in a regression model.

In statistical terminology, a multicollinear multiple regression model makes estimating the connection between independent and independent variables and dependent variables more complex. Small changes in the data or the model equation's structure might result in substantial and erratic changes in the estimated coefficients on the independent variables. While multicollinearity does not lower a model's overall predictive power, it can result in statistically insignificant regression coefficient estimations. In some ways, it's like double counting in the model. When two or more independent variables are closely related or measure almost the same thing, the underlying effect is accounted for twice (or more). It becomes difficult, if not impossible, to determine which variable has the most significant impact on the dependent variable.

CHAPTER 3

RESULTS AND DISCUSSIONS

3.1 Spatio-Temporal Landcover / Landuse Change

The findings demonstrate that forest area is declining with time, but the urban area is increasing. In years 1990 forest area is 931 km^2, the urban area is 5.1 km^2approximately and the grassland is 637 km^2, as shown in Figure 3.1, a. In 2000 values changed to98, 757.2, 1363 and 6.7 km^2 for agriculture, forest, grass and urban shown in Figure 3.1, b. In 2010, agricultural land increased to 112 km2, forest to 757 km2 and urban to 6.7 km^2 shownin Figure 3.1, c. In year 2021 forest area increased 893 km^2, the agriculture area increased to 294 km^2 and the urban area 14.6 km^2, whereas the waterbody decreased from 34 km^2 to 11 km^2 from 1990 to 2021 Figure 3.1, d. Accuracy assessment shows classification performed using a deep learning approach.

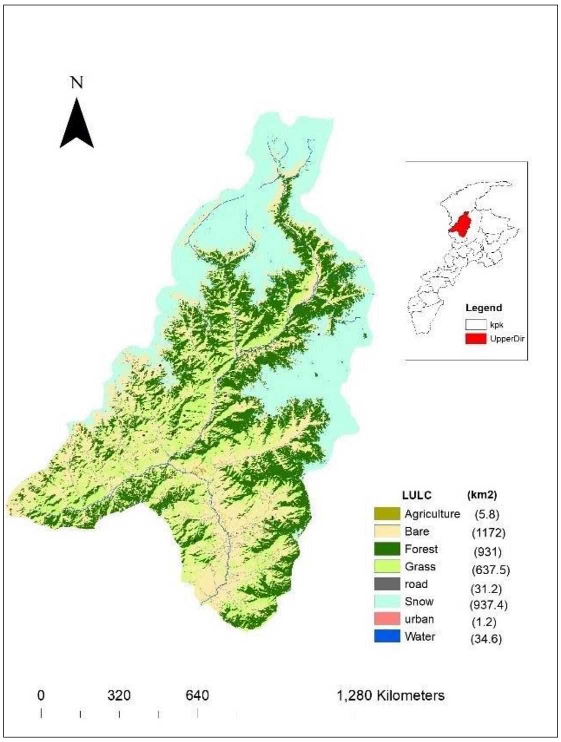
The population is continuously increasing from 1990 to 2021, and urbanization also increases with the increasing population, but forest area is decreasing till 2016, but there is some increase after 2017 because of afforestation. Moreover, demand for employment and food increased. Most people depend on agriculture for their earnings as the district's major area is the rural area. Most of the agricultural areas are present on hilly slopes and valleys as the population increases the number of households also increases; people are now performing agricultural activities near to their houses and cutting down forest land into agricultural land.

Forest area have been rapidly declining during past three decades, there is a visible change in the forest-covered region shown through the classificationof Landsat satellite imagery in Figure 3.2. According to the Kpk Forest department, forest boundaries remain the same. Only change can occur within the boundaries because of forest quality and quantity loss.

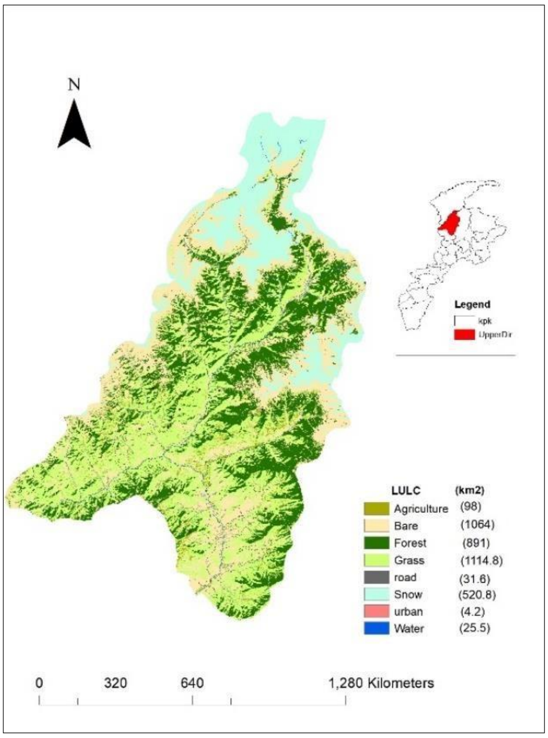
3.1.1. Accuracy Assessment of Landcover/Land use Change

Accuracy assessment shows deep learning model performs so well in terms of accuracy. The overall accuracy and kappa coefficient of year 1990 image are 88.4% and 85%, year 2000 image are 84.5% and 80.5%, year 2010 image are 87.5% and 84.1% and year 2021 image are 86.9% and 81.6%.

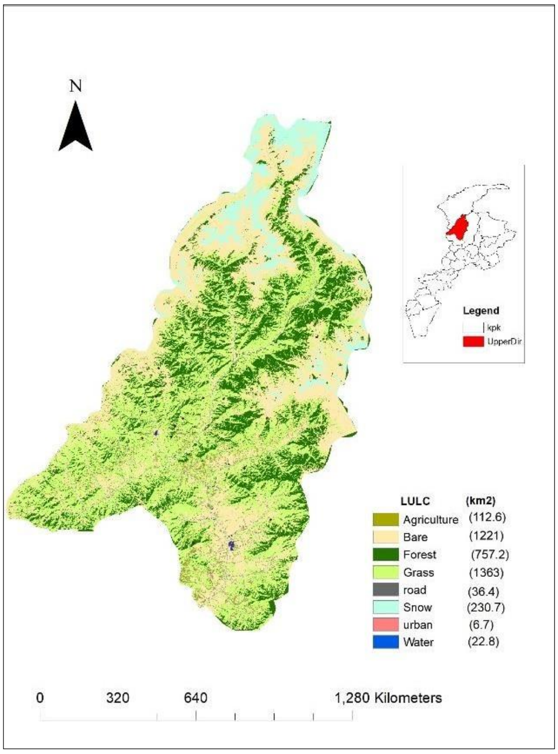
a.



b.



c.



d.

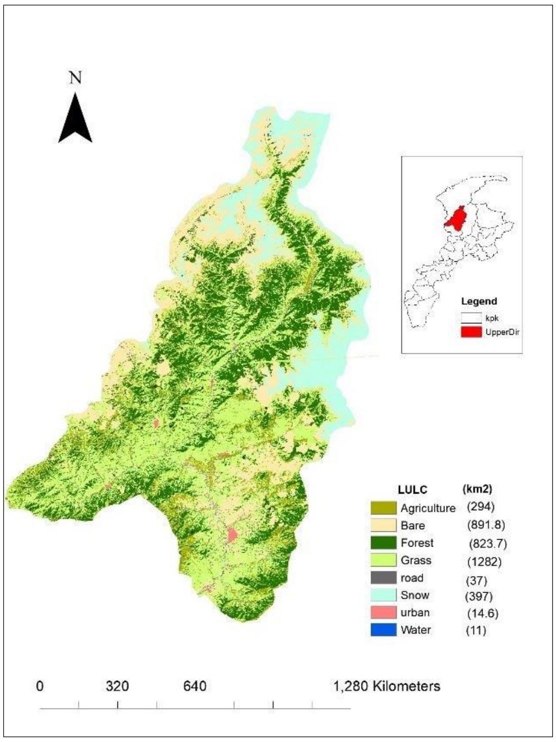


Figure 3.1, a. Classified map of year 1990, b. Classified map of year 2000, c. Classified mapof year 2010, d. Classified map of year 2021.

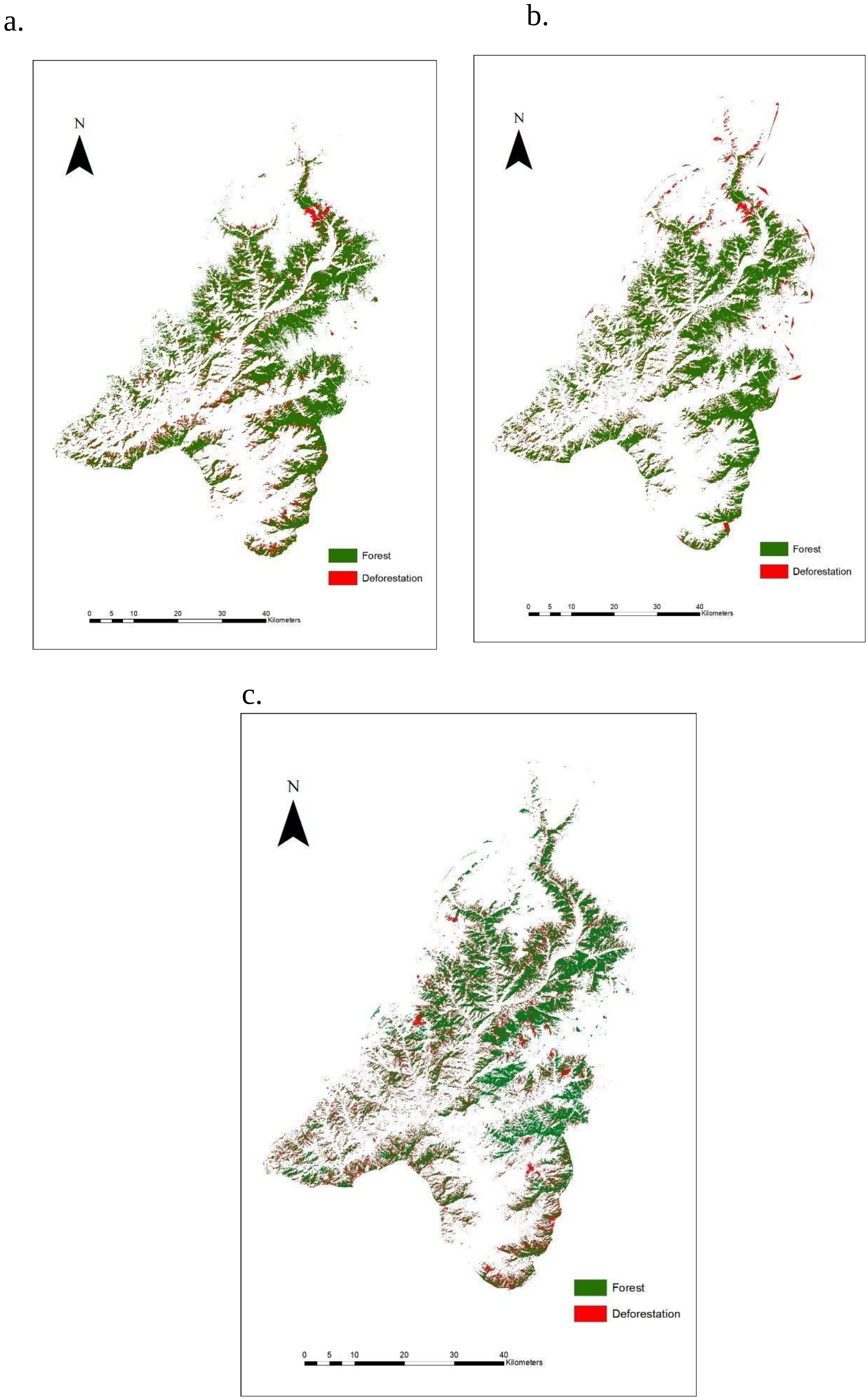


Figure 3.2. a. Deforestation occur from year 1990 to 2000, b. Deforestation occur from 2000 to2010, c Deforestation occur from 2010 to 2021.

3.2 Socioeconomic Survey

Pakistan's economy is not strong enough to convert from traditional fuel wood to modern fuels. Fuel wood accounts for roughly 53% of total annual household energy in Pakistan and is anticipated to stay high. Population growth and fuel wood usage are expected to increase by 3% per year. The rising demand for household fuel wood is expected to deplete forests quickly. On the question do you use gas cylinders at home for cooking and other purpose 70% of people from all UCs responded No, while 30% are using LPG/Gas Cylinders, as shown in Figure 3.3. Some households having Cylinders/LPG still consume firewoodas gas is not enough to fulfill their requirement.

Responses show that 71% of people are still not using gas cylinders, 15.8% started using after 2010, 6.6% started using after 2020 and 7% started using after 2000 illustrated in Figure 3.4. Many households are using gas as well as consuming forest wood for fire. Poor road infrastructure is one of the main reasons for lack of and poor access to energy alternatives like LPG/GAS. Roads are key for resources. Upper Dir locals mostly lives in a rural area where Lack of and poor access to markets contribute to firewood consumption. According to 70% of survey respondents, the main cause of deforestation in Upper Diris lack of alternate resources in which the main item is fuel wood. Oil, gas and other alternatives of wood for fuel. In year 2012-13 only 1% of people used gas and 0.83% used oil, and 97% used forest wood. In year 2014-15, according to PLSM survey report 100%locals are using wood as a fuel. In year 2019-20 70% use forest wood, 29% use forest wood, 29% use gas cylinders, and 1% use another alternative shown in Figure 3.5.

Deforestation assessment was conducted for the past 30 years with 10 years of interval to analyze forest cover trends. From year 1990 to 2000 forest area decreased but grass land and agriculture area increased, huge difference can be seen in both the land cover types after10 years gap. The agriculture area was 5km2 and in 2000 is became 98km2. That is a big difference.

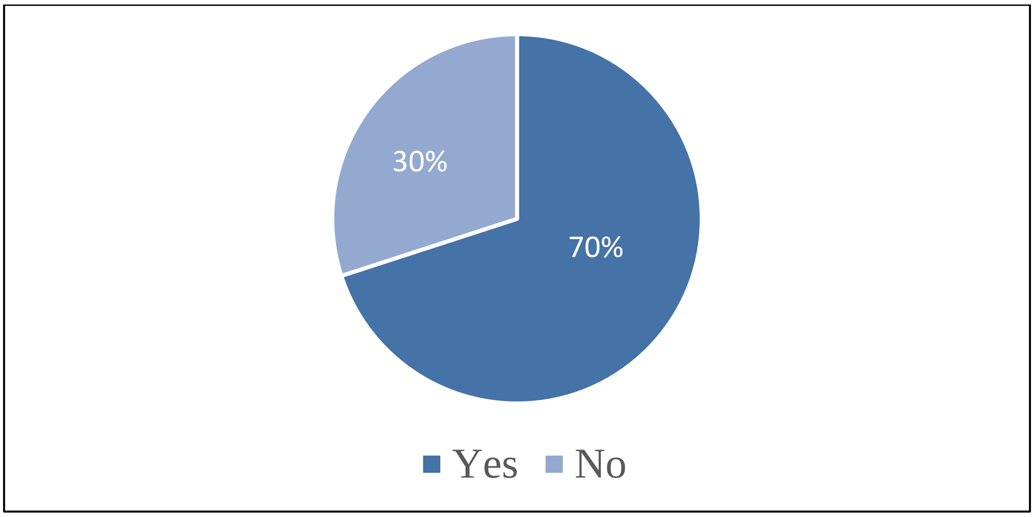


Figure 3.3. Graph showing responses for people using LPG/Gas.

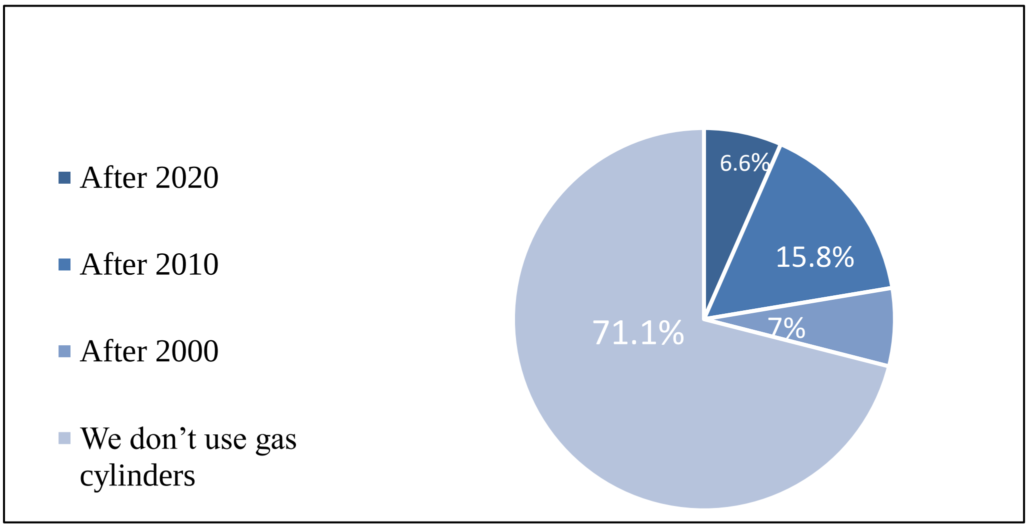


Figure 3.4. Graph showing responses for people since when they start using Gas/LPG.

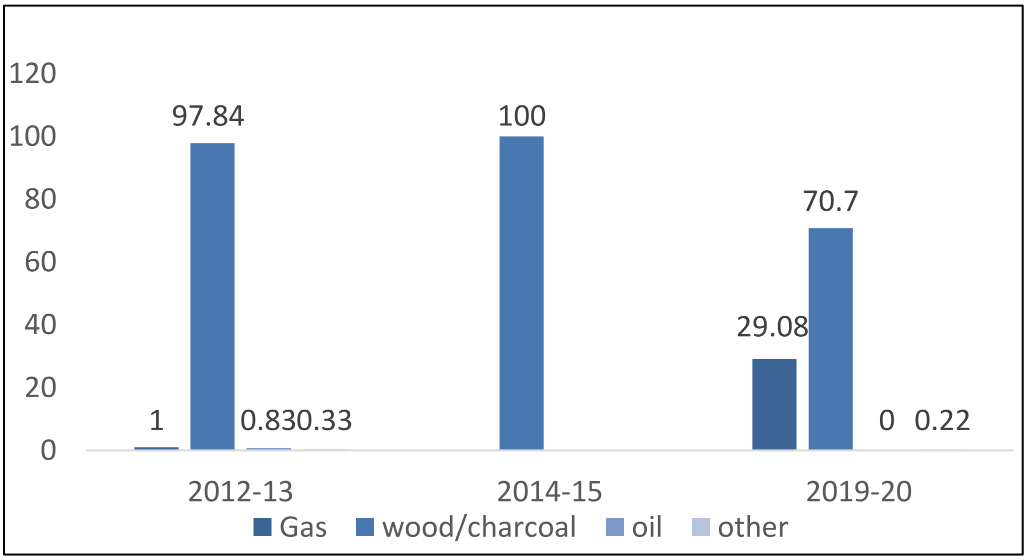


Figure 3.5. Alternatives of fuel and their usage percentage in past years.

About 70% of people responded that they consume forest wood for cooking purpose, as gas cylinders are not available to them, increasing population cause poverty. Locals do not have many resources to improve their living and support their families. If they are using gas cylinders, they still must use forest wood. As gas is not available to them in adequate quantity. 7.9% of people responded that they the forest for furniture making, they have fewer alternate options for employment as peoples are not well educated and there are no such big institutes and employment sources available to them. People who have education migrate towards big cities for employment. 17.3% are involved in the construction business 5% uses wood for other purpose shown in Figure 3.6.

From classified maps forest area decreases but population increases, so human activities also increase. Human behavior greatly influences natural resources as they depend onforest resources for their daily needs. Upper Dir district is rural-based people have not many resources to earn their living hence most of the population belongs to agriculture. Due to a lack of access to machinery andadvanced procedures and their exorbitant pricing, more land is consumed for lower yield output. As the population grows, so does the demand for food, increasing poverty.

Due to high food demand and less productivity people cut down forest land into agricultural land. Most of the people are not educated they have no option other than working in agriculture to earn their living apart from that, grazing is also related to agriculture activity it mostly affects small plants.

Upper Dir people depend on agriculture as their family business is agriculture. When asked 41% of respondents are currently involved in agriculture shown in Figure 3.7. Limited employment sources cause inadequate human and financial resources. Lack of technologies produce low-quality outcomes similarly due to the unavailability of heavy machinery and advanced techniques cropproduction is very low which cause more labor force to work in the field and a large area to beconsumed by agriculture. Lack of transportation facilities and mobility cause locals to earn their living by nearly available options like agriculture, construction, and other factors leadingto change in landcover due to human activities.

Another main cause of deforestation in Upper Dir is unemployment. The literacy rate of Upper Dir is low, resulting in local people's unemployment, which emphasizes pressure on them to involve in agriculture which is the only option left for them. Most of the young generation in Dir is illiterate and thus has very little employment opportunity. To fulfill their daily basic needs and requirements, the unemployed and jobless people of the area use these forests as a source of income in illegal manners. Poverty and overpopulation are believed to be the leading causes of forest loss, according to international agencies such as FAO and intergovernmental bodies.

Animal grazing also contributes to the loss of forests. Due to poor access to the market, 0.86% of people use forest resources for hay production. About 70% of respondents own livestock or have livestock around them shown in Figure 3.8 Overgrazing has reduced rangeland cover, which receives no investment or input to preserve its productivity and potential. Overgrazing has reduced rangeland cover, which receives no investment or input to preserve its productivity and potential. The livestock has twoeffects on the forests: they use the vegetation as fodder and graze on it. Second, vast herds of cattle and animals trample and crush the little plants. Overgrazing and cattle grazing contributes to deforestation and negatively affect forests in Dir.

Agriculture is the single most important driver of deforestation and forest degradation worldwide, with large-scale commercial agriculture accounting for 40% of tropical deforestation and rural subsistence agriculture responsible for another 33%. According to the United Nations Framework Convention on Climate Change, deforestation is mostly driven by cutting trees to expand agriculture. Many local small farmers cut down trees each year to clear a few acres for their families to feed them, then burn them in a method known as "slashand burn" agriculture. Others clear areas for growing crops, ranches, and other food-producingplaces by cutting down trees. Subsistence agriculture is the primary source of rangeland forest degradation. There is widespread agreement that poverty is a primary source of population increase and environmental degradation and that population expansion, on the other hand, is a major cause of poverty and environmental degradation, such as pollution and deforestation.

The rate of deforestation is dramatically increased by road construction and increased agricultural activities. Forest degradation and destruction, primarily due to increased agricultural activity in tropical developing countries, accounts for about 12% of global greenhouse gas emissions. Deforestation is accelerated by access to roads, rivers, railroads, forests, and markets. Forest fragments are also more accessible than large, dense forests, and forests in coastal and inland areas are more accessible than others. Deforestation is slowing in all those forests 2 or 3 kilometers away from the road.

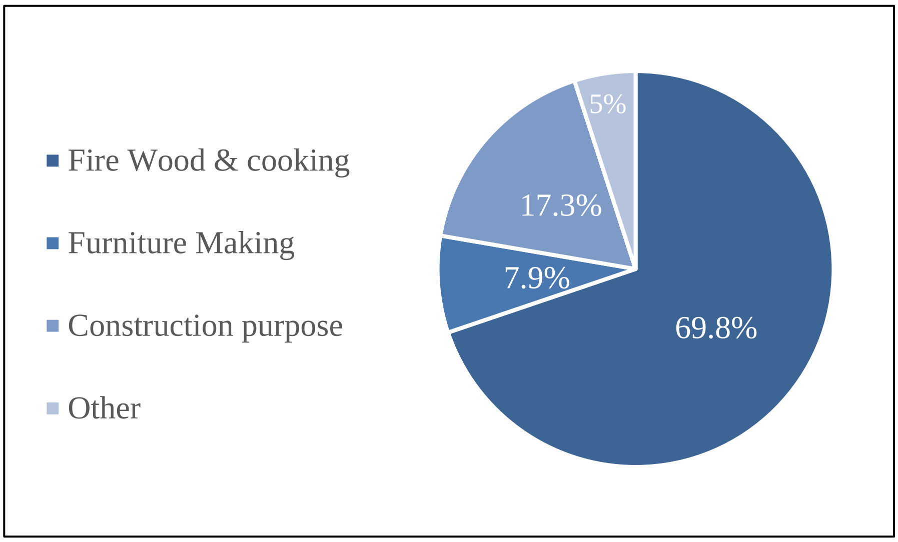


Figure 3.6. Responses for major activities causing deforestation.

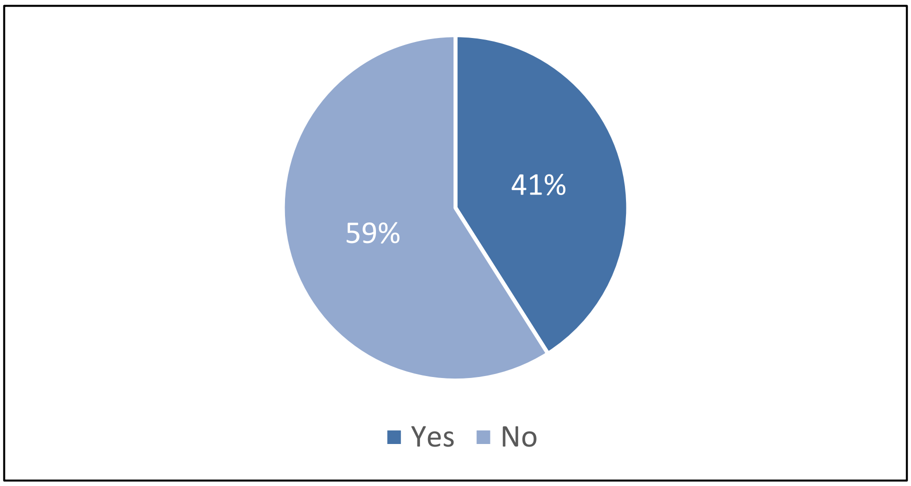


Figure 3.7. Responses of people involved in agriculture.

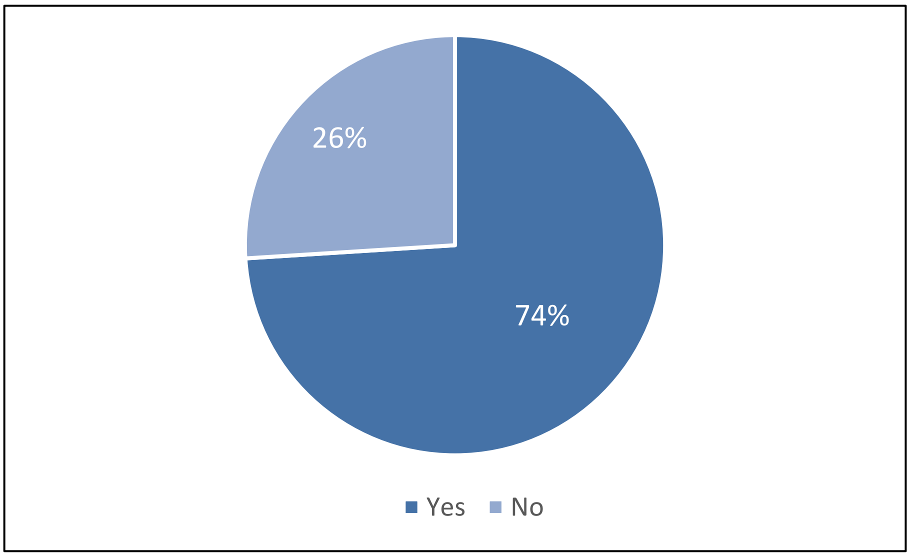


Figure 3.8. Do you or people in your area have livestock?

Forests are destroyed to accommodate developing urban areas, another driver of deforestation. To make room for growing urban areas, the forest is cleared. Harvesting trees for paper, building materials, and furniture severely impact forest life. As a result, there is significant deforestation and forest loss. Wood consumption and production have a significant disparity.

The purpose may be to sell illegally; loggers and timber mafia cut down trees and sell them in the market. Due to a lack of employment and resources, people have to support their families through illegal work. The main drivers of environmental deterioration and deforestation are poverty, population expansion, and other problems such as bad governance, income disparity, and sluggish economic growth. Poverty has increased higher in rural areas of Pakistan than in metropolitan ones. In the 1990s, rural poverty increased rapidly, and rural poverty (36.3 percent) was higher than urban poverty in 1999. (22.6%). According to the most recent figures,the poverty headcount ratio was 29.2% in 2004-05 and 36.1% in 2008-09.

To get more financial benefits, they build roads to access more and more remote forests causing further deforestation. Upper Dir residents use wood for household and business purposes, such as furniture in hotels, shops, and homes. Due lack of literacy and skills there are only few major employment opportunities available to them, about 45% of population is involved in agriculture and 22% is involve in construction shown in Figure 3.9. 30% people in upper Dir have furniture businesses shown in Figure 3.11., which increases the demand for tons of furniture wood. They do not use any alternative for timber, such as using plastic commodities instead of wooden furniture. Due to the high demand of timber and Shesham wood illegal logging for demanding wood occur, forest loss its quality and loss in a variety ofspecies occur, which is a great loss of country natural resources with the economical point of view.

To fulfill their daily basic needs and requirements the unemployed and jobless people of the area use these forests as a source of income in illegal manners. According to international organizations such as the FAO and intergovernmental bodies, poverty and overpopulation are the primary drivers of forest loss. Poverty and pollution are all linked. Population growth is the primary cause of forest loss, which leads to several issues such as increased food demand, a high demand for landfor housing, conversion of forest land to urban and agricultural areas, and limited resource availability. As the population and poverty levels rise, the area becomes more polluted, and the natural environment degrades. Construction of roads and infrastructure development do not directly cause loss in forest as government won't construct roads within forest area boundaries 60% people responded that construction of roads do not influence deforestation shown in Figure 3.13.

According to 60.5 percent of the respondents, forest wood is extensively employed to construct new and repair existing dwellings. Wood is used to construct most of the dwellings in all communities. Even if the house is made of mud/stones or brick, lumber is required for roofs, doors, and other structures. Due to a lack of wood substitutes and, limited resource availability for building construction, and inefficient use of wood in buildings leads to a high forest dependency on timber, which leads to timber logging and illegal tree cutting for construction purposes. As people in the upper Dir still live in wooden roof houses, they don't have enough money to construct building door windows with other substitutes as it would cost them a fortune. Figure 3.14. illustrates the percentage of material used for construction.

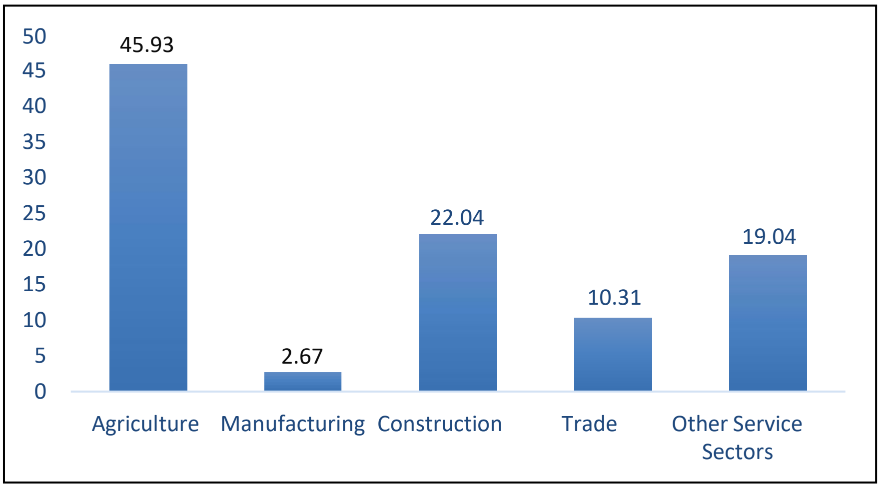


Figure 3.9. Major sectors for the employed labor force.

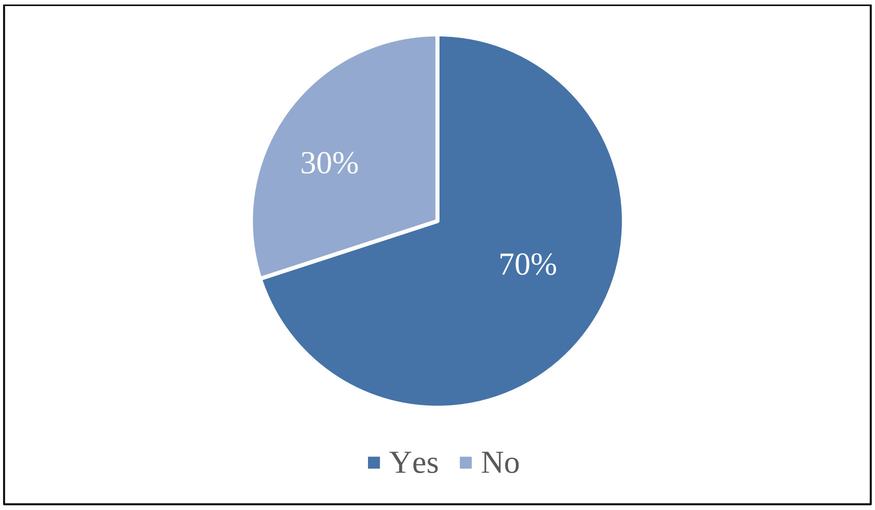


Figure 3.10. Responses of people about road construction.

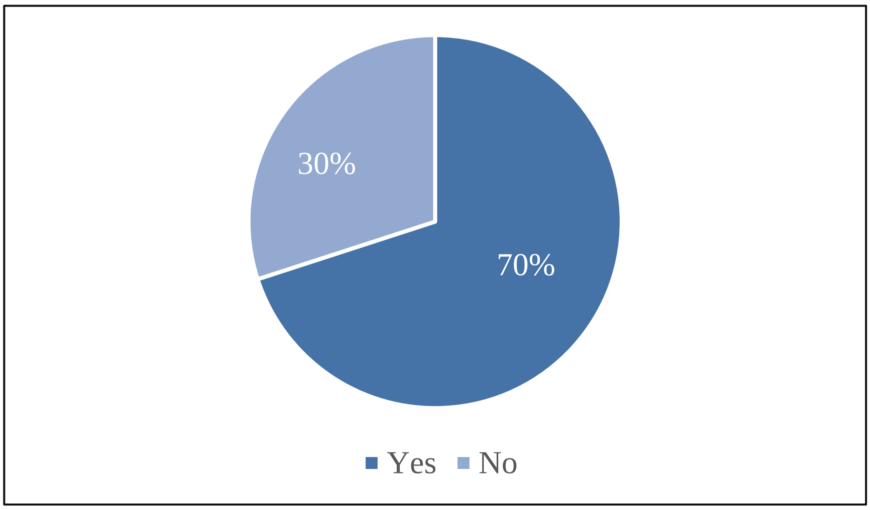


Figure 3.11. Responses of people having furniture business.

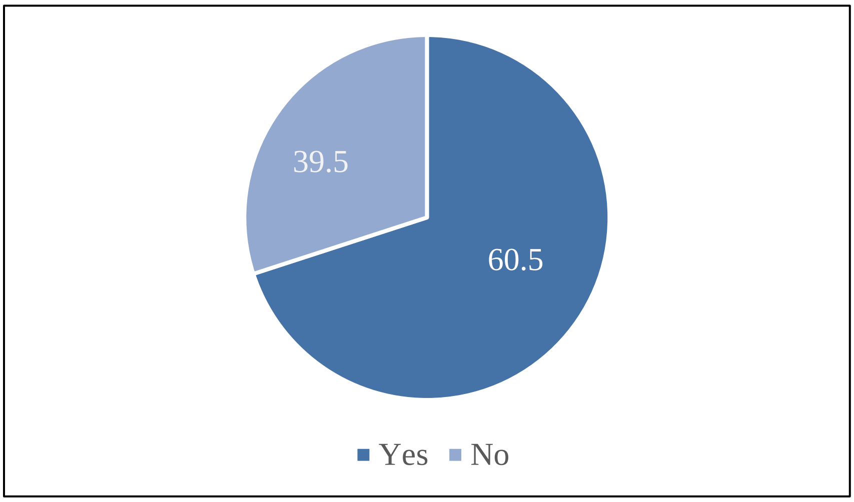


Figure 3.12. Responses to estimate infrastructure development.

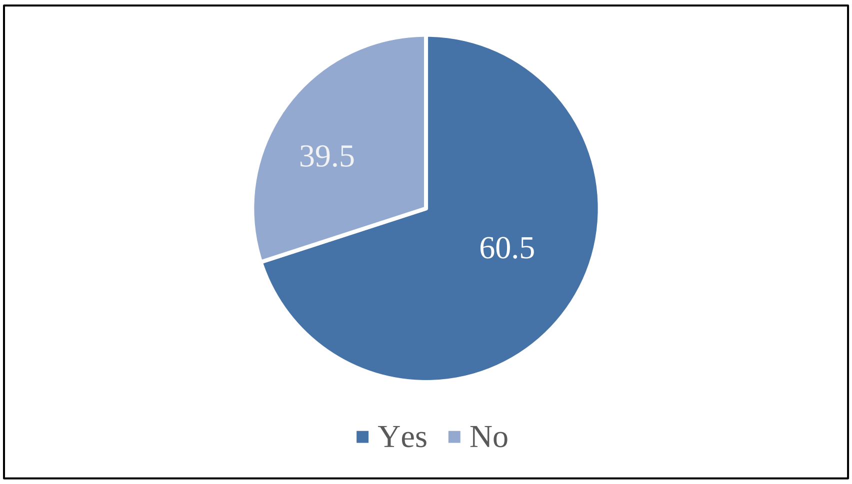


Figure 3.13. Responses for impact of construction on deforestation.

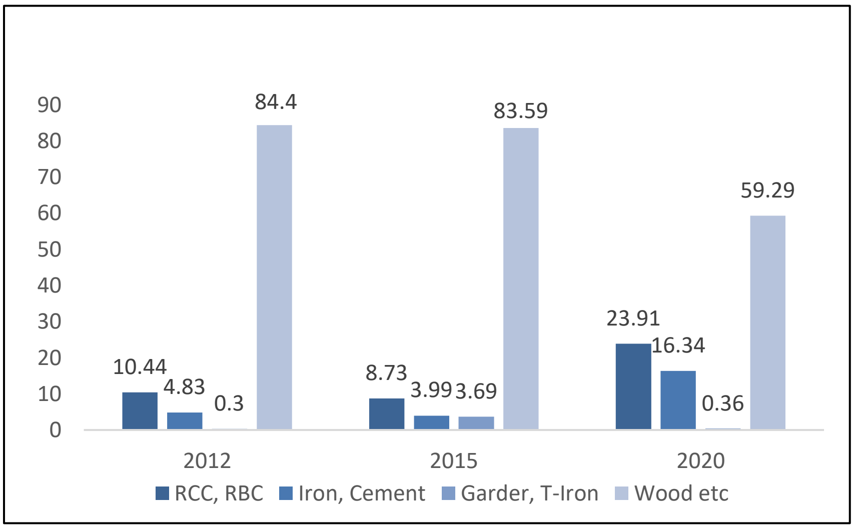


Figure 3.14. Graph of Construction material used in Upper Dir.

3.3 Deforestation Drivers

It is estimated deforestation is caused by firewood consumption, animal grazing, urbanization, agricultural development, and population growth. Forest cover value decreases in UCs with increasing urban areas. In the same way, vast agricultural areas have a high deforestation value. The same can be said for population growth and livestock grazing. The model includes road distance as a significant component in deforestation. Still it is an iterative process in which all effects are entered and removed until all relevant impacts are gathered. Remove any variables that are linked or non-significant.

Data on urbanization, grazing, and firewood usage do not indicate collinearity and are all significant, thus we may do regression analysis with just these variables. It is common knowledge that agriculturally productive places have more cattle and grazing opportunities. When the population of a region grows, so does the demand for food, thus, people cut down more trees to cultivate crops for food and profit. As a result, this fact can be derived from the basic assumption that agriculture and population are linked, and that agriculture is linked to grazing.

In a multiple regression model, multicollinearity refers to a high degree of linear intercorrelation between explanatory variables, which leads to inaccurate regression findings. The variance inflation factor (VIF), condition index and condition number, and the Proportion of Variance are all diagnostic tools for multicollinearity (PoV). The coefficient of determination (Rh2) of a multiple regression model with one dependent variable and the other explanatory variables can be used to express multicollinearity. The bigger the VIF, the more untrustworthy the regression coefficients' probability values and confidence intervals are.

The greater CI is 5.41, with 98.5 percent and 50.9 percent firewoodand urban variances. There is no multicollinearity because 5.4 is less than 10. Because there are four predictors, the total eigenvalue is four. Multicollinearity is evident when the VIF is greater than 5 to 10 or the condition indices are greater than 10 to 30. The condition index is the square root of the ratio of the greatest eigenvalue to each eigenvalue from the correlation matrix of standardized explanatory variables. The maximum condition index is the condition number. The best fit criterion value for model shown in Figure 3.16. according to AIC and AICc, firewood, grazing and urban area are enough to describe significantrelationship between socio-economic factors and deforestation. Correlation coefficient graph also shows that firewood consumption is the most significant variable after that is grazing and then urban area expansion is significantly contributing to deforestation shown in Figure 3.17. Agriculture and population are also significant but contributing to redundancy shown in Table 3.1. Significantly contributing factors with multicollinearity are not included in model shown in Table 3.5. to eliminate redundancy variables should have VIF value less than 2.5, less than 4 is also acceptable but more than 4 shows high multicollinearity. Table 3.6. shows variables with VIF value less than 2.5. are firewood consumption, animal grazing and agriculture expansion. BIC, Cp, PRESS, SBC all criterion graphs show same result except Adjusted R^2 which added all significant effects to the model.

For any model there are some points that must be checked; residuals are equally distributed they are independent of each other there is no correlation between residuals. There must be no redundancy in the data values, there must be a linear relationship between independent and dependent variables. If any of these assumptions are avoided, then the model will be incorrect. Predicted and observed values for dependent variables must be similar; they must coincide on a single straight line.

Table 3.1. Stepwise regression model selection summary.

Stepwise Selection Summary											
Step	Effect Entered	Effect Removed	Number Effects In	Model R-Square	Adjusted R-Square	AIC	AICC	BIC	CP	F Value	Pr>F
0	Intercept		1	0.0000	0.0000	-121.8	-121.389	-155.9	177.68	0.00	1.0000
1	fire_wood		2	0.7184	0.7087	-159.105	-158.216	-192.411	31.2003	73.99	<.0001
2	grazing		3	0.8472	0.8363	-176.04	-174.511	-207.16	6.58	23.59	<.0001
3	Avg_urban		4	0.8803	0.8670	-181.62*	-179.223*	-210.72	1.740*	7.47	0.0109
4	Avg Agri		5	0.8867	0.8692	-181.31	-177.815	-209.29	2.4269	1.46	0.0381
5	Pop 2021		6	0.8928	0.8713*	-181.02	-176.159	-207.56	3.1668	1.42	0.0444
*Optimal Value of Criterion											

Table 3.2. Analysis of variance for deforestation drivers.

Analysis of Variance					
Source	DF	Sum of Squares	Mean Squares	F Value	Pr > F
Model	3	0.17340	0.05780	69.19	<0.0001
Error	27	0.02358	0.00087327		
Corrected Total	30	0.19698			

Table 3.3. Criterion values for model selection.

Root MSE	0.029
Dependent Mean	0.081
R-Square	0.88
Adj R-Square	0.867
AIC	-181.623
AICC	-179.22
BIC	-210.72
C(p)	1.740
PRESS	0.036
SBC	-208.88
ASE	0.00076

Table 3.4. Parameter estimation of the stepwise regression model.

Parameter Estimate					
Parameter	DF	Estimate	Standard error	T value	Pr >|t|
Intercept	1	-0.105	0.023	-4.55	0.0001

Table 3.5. SAS result for the proportion of variance among independent variables.

Number	Eigenvalue	Condition Index	Proportion of Variation			
			intercept	fire_wood	grazing	Avg_urban
1	3.200	1.000	0.0046	0.0032	0.032	0.017
2	0.392	2.864	0.037	0.0111	0.645	0.043
3	0.376	2.901	0.011	0.000003	0.322	0.429
4	0.02	5.410	0.948	0.985	0.00003	0.509

Table 3.6. Collinearity diagnostic of significant variables.

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Tolerance	Variance Inflation
Intercept	1	-0.105	0.02	-4.55	0.0001		0
Fire_wood	1	0.002	0.0005	5.28	<.0001	0.432	2.311
Grazing	1	0.007	0.0015	4.79	<.0001	0.875	1.136
Avg_urban	1	1.279	0.4679	2.73	0.0109	0.419	2.383

Table 3.7. Correlation coefficients of deforestation drivers.

Pearson's Correlation Coefficient N=31										
	Average deforestation	**Id**	**construction**	**Firewood consumption**	**Grazing**	**Gas per UC**	**Average road**	**Urban area**	**Agriculture area**	**population**
Average Deforestation	1	0.10	0.47	0.84	0.59	-0.7	-0.2	0.79	0.82	0.06
Id	0.10	1	-0.05	0.118	0.11	-0.2	-0.1	0.16	0.10	-0.2
Construction	0.47	-0.0	1	0.38	0.31	-0.2	-0.05	0.57	0.39	0.13
Firewood consumption	0.84	0.12	0.38	1	0.28	-0.6	-0.12	0.75	0.81	-0.14
Grazing	0.59	0.11	0.31	0.2	1	-0.48	-0.2	0.34	0.46	0.29
Gas per UC	-0.729	-0.2	-0.29	-0.69	-0.48	1	0.47	-0.6	-0.81	-0.12
Average road	-0.22	-0.1	-0.05	-0.12	-0.24	0.47	1	-0.17	-0.47	-0.06
Urban area	0.79	0.16	0.57	0.75	0.34	-0.68	-0.1	1	0.66	0.11
Agriculture area	0.82	0.10	0.39	0.81	0.46	-0.8	-0.47	0.66	1	-0.08
population	0.06	-0.2	0.135	-0.14	0.29	-0.1	-0.06	0.11	-0.08	1

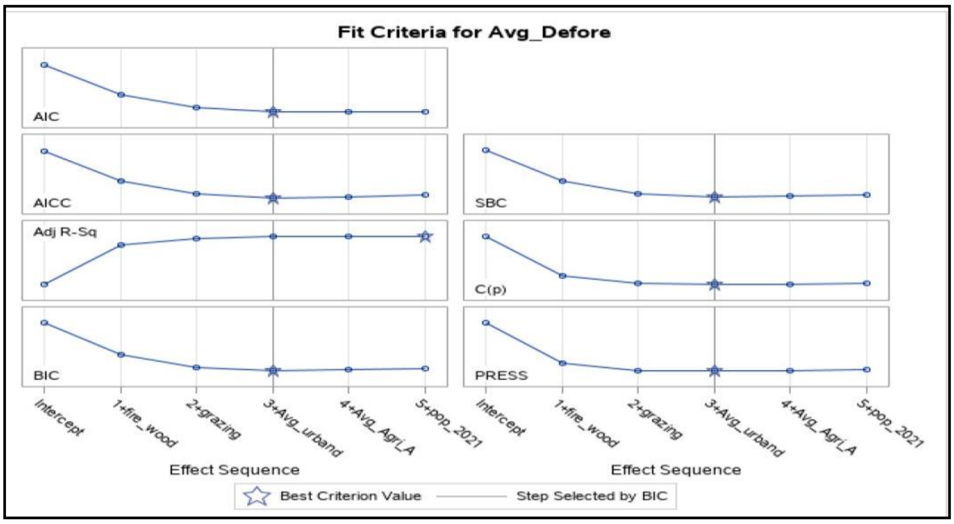


Figure 3.15. Best criterion Value Graph.

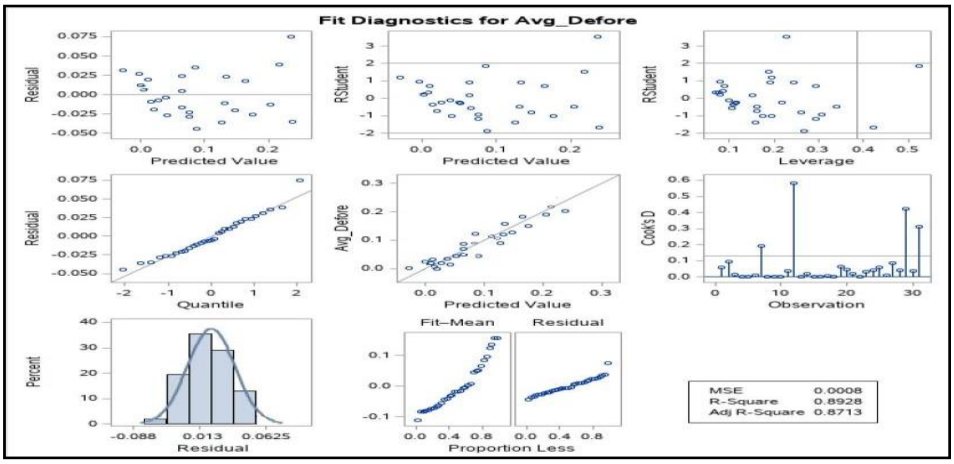


Figure 3.16. Fit diagnostic graphs for explanatory variables.

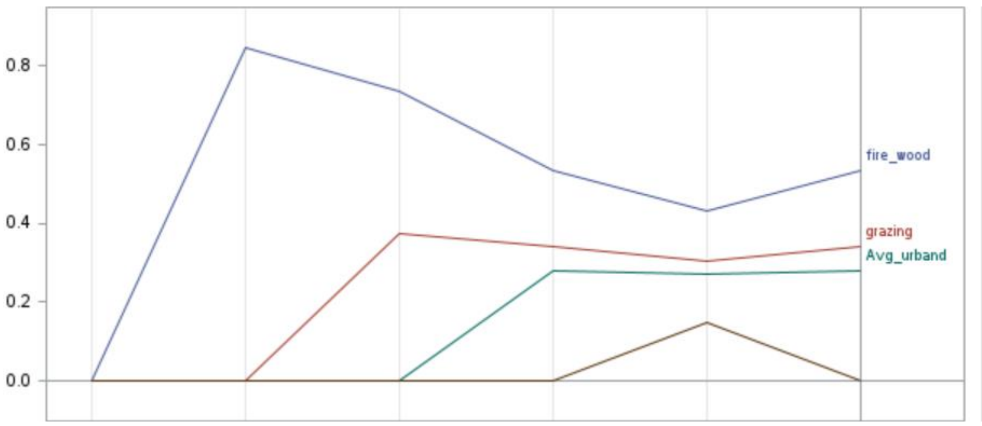


Figure 3.17. Standardized coefficient of regression.

CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusion

It is concluded from the current study that from 1990 to 2000 3.5 percent of total forest area had been lost and 2.58 percent agricultural area and 0.08 percent of the urban area has increased in upper Dir district. From the 2000 to 2010 2.1 percent of total forest area decreased, 0.36 percent of agriculture land increased, and 0.07 percent of total area was included in urban. From 2010 to 2021 because of BTTAP 2016- & 2017-1.9 percent increase in forest area, 5.1 percent increase in agriculture area and 0.22 percent of the total area added to urban area. The major drivers which significantly ($p<0.05$) contributed to deforestation were firewood, grazing animals, urban expansion, agriculture expansion and population growth. While construction of roads, infrastructure development, gas usage did not significantly ($p<0.05$) contribute to the deforestation in the study area.

4.2 Recommendations

Deforestation is a problem that may be avoided, and you can help. The following efforts should be taken to prevent deforestation and its negative repercussions. To limit the adverse effects of deforestation and save this ecosystem, government authorities must address the underlying reasons of deforestation in Upper Dir by enacting strong rules and regulations, raising environmental awareness, and providing alternativeresources. Due to the high incidence of deforestation and increased rural activities, it is suggested that a mindfulness war be launched in the research region to protect and ration this forest from future devastation. Household characteristics are highly correlated with the amount of land cleared throughout time. To maintain and increase afforestation survival rates, we should grow plant species that are more suited to the local climatic, geographical, and topographical circumstances. The government should give resources to the local community to learn new skills and discover alternative forms of income other than forest cutting. Govt must provide energy sources to the district by subsidizing the gas cylinders so that people can afford them, automatically decrease their dependence on forest wood for fuel. As most people are involve in agriculture, they have cattle we can also install biogas plants to produce energy and provide funding and awareness among people to use advanced machinery and techniques for better agriculture growth and provide pesticides and fertilizers at reasonable prices to them to increase productivity and repair degraded agriculturalland. There should be strong coordination between different forest, land revenue and agriculturedepartment. Reduce the amount of wood used in construction, furniture, and other items by providing easy access to market and lowering the cost of this material. The government must end forest department bribery across Pakistan, prohibit smuggling, and punish the wood mafia.

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APPENDICES

APPENDICES

Appendix 1a. Socio-economic Survey Data Collection

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you startedusing LPG/ Gas cylinder at home?	Do you involve in agriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people aroundyou have livestock?
2/24/2022 5:13:24	Dir	Dir	No	After 2020	No	No	No
2/24/2022 8:27:19	Dir	Dir	No	We don’t use gas cylindersat home.	Yes	Yes	Yes
2/24/2022 9:13:09	Dir	Dir	Yes	After 2020	Yes	Yes	Yes
2/24/2022 9:19:06	Dir	Dir	No	We don’t use gas cylindersat home.	Yes	Yes	Yes
2/24/2022 9:23:32	Dir	Dir	No	We don’t use gas cylindersat home.	Yes	Yes	Yes
2/24/2022 10:05:40	Dir	Dir	No	We don’t usegas cylinders at home.	Yes	Yes	No
2/24/2022 10:21:47	Dir	Dir	No	We don’t use gas cylindersat home.	No	No	No
2/24/2022 10:27:17	Kalkot	Gwaldai	No	We don’t use gas cylindersat home.	No	No	Yes
2/24/2022 10:45:24	Dir	Dir	No	We don’t use gas cylindersat home.	No	Yes	Yes
2/24/2022 10:53:47	Dir	Dir	Yes	After 2000	No	Yes	No
2/24/2022 10:53:52	Dir	Dir	Yes	After 2010	No	No	Yes
2/24/2022 10:53:55	Dir	Dir	No	We don’t use gas cylindersat home.	No	No	No
2/24/2022 10:54:32	Dir	Dir	Yes	After 2010	Yes	Yes	Yes
2/24/2022 10:55:04	Dir	Dir	No	We don’t use gas cylindersat home.	Yes	Yes	Yes

Continue…………

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you started using LPG/ Gas cylinder at home?	Do you involve inagriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people around you have livestock?
2/24/2022 10:55:08	Dir	Dir	Yes	After 2010	No	No	Yes
2/24/2022 11:14:01	Dir	Doagdara	No	We don’t use gas cylinders at home.	No	No	Yes
2/24/2022 11:30:17	Dir	Dir	No	We don’t use gas cylinders at home.	Yes	Yes	Yes
2/24/2022 11:32:11	Dir	Dir	No	We don’t use gas cylinders at home.	Yes	Yes	Yes
2/24/2022 11:35:25	Dir	Dir	Yes	After 2020	No	Yes	Yes
2/24/2022 19:20:10	Wari	Dir	No	We don’t use gas cylinders at home.	No	Yes	Yes
2/24/2022 19:22:16	Wari	Dir	No	We don’t use gas cylinders at home.	No	Yes	Yes
2/24/2022 19:33:00	Dir	Dir	No	We don’t use gas cylinders at home.	No	Yes	Yes
2/24/2022 23:43:59	Kalkot	Dir	No	We don’t use gas cylinders at home.	Yes	Yes	Yes
2/25/2022 0:46:28	Dir	Dir	Yes	2000 کے بعد	No	No	No
2/25/2022 2:15:57	Kalkot	Kalkot	No	We don’t use gas cylinders at home.	Yes	Yes	Yes
2/25/2022 18:34:37	Dir	Darora	Yes	After 2000	Yes	Yes	Yes
2/26/2022 23:11:49	Dir	Taraptar	No	We don’t use gas cylindersat home.	No	No	Yes
2/25/2022 18:34:37	Dir	Darora	Yes	After 2000	Yes	Yes	Yes
2/26/2022 23:11:49	Dir	Taraptar	No	We don’t use gas cylindersat home.	No	No	Yes

Continue…………

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you startedusing LPG/ Gas cylinder at home?	Do you involve inagriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people aroundyou have livestock?
2/25/2022 3:52:04	Dir	Taraptar	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/25/2022 4:58:13	Kalkot	Kalkot	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/25/2022 5:44:36	Dir	Darora	Yes	We don't use gas cylinders at home.	No	No	Yes
2/25/2022 6:07:10	Kalkot	Chikanan	No	We don't use gas cylinders at home.	No	No	Yes
2/25/2022 6:10:06	Dir	Doagdara	No	We don't use gas cylinders at home.	No	No	No
2/25/2022 6:21:39	Dir	Dir	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/25/2022 9:11:20	Dir	Gwaldai	No	We don't use gas cylinders at home.	No	No	Yes
2/28/2022 7:44:37	Wari	Bandi Nehag	Yes	After 2020	Yes	Yes	Yes
2/28/2022 20:04:25	Wari	Akhagram	No	We don't use gas cylinders at home.	Yes	Yes	No
2/28/2022 23:39:20	Dir	Wari	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/27/2022 3:47:08	Dir	Wari	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/27/2022 8:46:40	Wari	Bandi Nehag	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/28/2022 7:22:01	Wari	Wari	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/27/2022 3:36:57	Dir	Bandi Nehag	No	We don't use gas cylinders at home.	Yes	Yes	Yes

Continue**……..**

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you started using LPG/ Gas cylinder at home?	Do you involve inagriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people aroundyou have livestock?
2/26/2022 23:13:14	Dir	Wari	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/27/2022 0:32:59	Dir	Wari	No	After 2010	No	No	No
2/27/2022 1:21:21	Wari	Wari	No	We don't use gas cylinders at home.	Yes	Yes	Yes
2/27/2022 1:31:51	Wari	Toormang	No	We don't usegas cylinders at home.	Yes	No	No
2/27/2022 2:33:10	Wari	Darora	Yes	After 2000	No	No	Yes
3/3/2022 10:51:46	Dir	Bibiawar	Yes	After 2020	No	Yes	No
3/3/2022 23:20:19	Dir	Bibiawar	No	We don't use gas cylindersat home.	Yes	Yes	Yes
¾/2022 6:53:16	Wari	Kotkai	No	We don't use gas cylinders at home.	Yes	Yes	Yes
3/3/2022 10:43:10	Barawal	Darikund	Yes	After 2010	No	No	No
3/3/2022 10:45:37	Dir	Ganori	Yes	After 2010	No	No	Yes
3/3/2022 10:46:36	Dir	Ganori	Yes	After 2010	Yes	Yes	Yes
3/3/2022 10:38:34	Barawal	Shahikot	No	We don't use gas cylinders at home.	Yes	Yes	Yes
3/3/2022 10:41:54	Barawal	Darikund	Yes	After 2010	No	No	No

Continue……..

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you started using LPG/ Gas cylinder at home?	Do you involve inagriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people aroundyou have livestock?
3/1/2022 22:13:34	Wari	Akhagram	No	We don't usegas cylinders at home.	Yes	Yes	Yes
3/2/2022 6:45:03	Wari	Bandi Nehag	No	We don't use gas cylindersat home.	No	No	No
3/3/2022 10:29:45	Wari	Khalshflam	Yes	After 2010	No	No	No
3/3/2022 10:34:51	Wari	Wari	No	We don't use gas cylindersat home.	Yes	Yes	Yes
3/3/2022 10:36:12	Barawal	Barawal	No	We don't use gas cylindersat home.	No	No	No
3/6/2022 8:57:43	Wari	Nihag dara	Yes	After 2010	Yes	Yes	Yes
3/6/2022 9:04:06	Wari	Nihag dara	No	We don't use gas cylinders at home.	No	Yes	Yes
3/6/2022 9:07:08	Wari	Sandul	No	We don't usegas cylinders at home.	No	No	No
3/6/2022 8:54:51	Wari	Chapper	No	We don't usegas cylinders at home.	No	No	Yes
3/6/2022 8:52:17	Wari	Chapper	No	We don't use gas cylinders at home.	No	No	Yes
4/3/2022 9:20:00	Wari	Daslawar	Yes	After 2020	Yes	No	No
4/3/2022 9:20:00	Wari	Daslawar	Yes	After 2020	Yes	No	No

Continue……..

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you started using LPG/ Gas cylinder at home?	Do you involve inagriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people aroundyou have livestock?
3/6/2022 8:17:42	Dir	Doagdara	Yes	After 2010	Yes	Yes	Yes
3/6/2022 8:21:14	Wari	Wari	No	We don't use gas cylindersat home.	No	Yes	Yes
3/6/2022 8:24:54	Wari	Bandi Nehag	No	We don't use gas cylinders at home.	Yes	Yes	Yes
3/6/2022 8:47:46	Wari	Pashta	Yes	After 2010	Yes	Yes	Yes
3/6/2022 8:48:47	Wari	Akhagram	No	We don't use gas cylindersat home.	No	No	No
3/11/2022 8:48:07	Dir	Patrak	No	We don't use gas cylinders at home.	Yes	Yes	Yes
3/18/2022 6:15:05	Dir	Patrak	Yes	After 2000	Yes	Yes	Yes
4/3/2022 4:58:10	Dir	Wari	No	We don't use gas cylinders at home.	Yes	Yes	Yes
4/3/2022 5:03:20	Dir	Dir	No	After 2000	No	No	No
4/3/2022 5:05:06	Wari	Bandi Nehag	Yes	We don't use gas cylinders at home.	No	No	Yes
4/3/2022 5:06:49	Barawal	Barawal	Yes	We don't use gas cylinders at home.	Yes	Yes	Yes
2/25/2022 9:25:31	Kalkot	Dir	No	We don't use gas cylinders at home.	Yes	Yes	Yes
4/3/2022 9:18:43	Wari	Bandi Nehag	Yes	After 2020	Yes	Yes	Yes

Continue……...

Time stamp	In which Tehsil do you live?	In which Union Council doyou live?	Do you use gas cylinderat home for cooking and	Choose year when you started using LPG/ Gas cylinder at home?	Do you involve inagriculture?	Do any of your family member and other people from your surroundingswere involved in agriculture in previous years?	Do you and people aroundyou have livestock?
4/3/2022 5:10:01	Dir	Chikanan	No	After 2010	Yes	Yes	No
4/3/2022 5:13:56	Wari	Khalshflam	No	After 2020	Yes	Yes	Yes
4/3/2022 5:17:04	Wari	Kotkai	Yes	We don't use gas cylindersat home.	No	No	Yes
4/3/2022 5:19:17	Dir	Bibiawar	Yes	We don't use gas cylindersat home.	No	No	No
4/3/2022 5:21:27	Dir	Gwaldai	No	We don't use gas cylindersat home.	Yes	No	No
4/3/2022 8:34:35	Dir	Barikot	No	After 2000	No	Yes	No
4/3/2022 8:36:25	Dir	Toormang	Yes	We don't use gas cylindersat home.	Yes	Yes	Yes
4/3/2022 8:38:27	Wari	Sandul	Yes	We don't usegas cylinders at home.	Yes	Yes	Yes
4/3/2022 8:40:52	Dir	Patrak	No	After 2010	Yes	Yes	No
4/3/2022 8:43:26	Dir	Darikund	No	We don't usegas cylinders at home.	Yes	No	Yes
4/3/2022 8:45:23	Dir	Ganori	Yes	We don't use gas cylindersat home.	Yes	No	Yes
4/3/2022 9:05:48	Barawal	Kalkot	No	We don't usegas cylindersat home.	Yes	No	Yes
4/3/2022 9:07:53	Dir	Taraptar	No	After 2020	Yes	Yes	Yes
4/3/2022 9:10:52	Wari	Barawal	No	After 2020	Yes	Yes	Yes

Appendix 1b. Socio-economic Survey Data Collection.

In your opinion, which activityis consuming large amount of forest wood or resources in your area?	Do anyone from your surrounding have furniture	Is there any constructionof roads in your area?	Is there any construction work done in your area after 2010?	Do you think construction of more houses cause	Have trees been planted in your area?
For furniture making	Yes	Yes	Yes	Yes	No
For construction	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	No
Cooking and firewood consumption	No	No	Yes	No	Yes
Cooking and firewood consumption	No	No	Yes	No	Yes
Cooking and firewood consumption	No	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	No
Cooking and firewood consumption	No	No	No	No	Yes
Cooking and firewood consumption	Yes	No	No	Yes	No
For furniture making	Yes	Yes	Yes	Yes	No
For construction	Yes	No	Yes	No	No
For furniture making	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	No	Yes	No
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
We don't use forest wood	No	No	No	No	Yes
Cooking and firewood consumption	No	No	No	No	Yes

Continue……

In your opinion, which activityis consuming large amount of forest wood or resources in your area?	Do anyone from your surrounding have furniture	Is there any constructionof roads in your area?	Is there any construction work done in your area after 2010?	Do you think construction of more houses cause	Have trees been planted in your area?
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	Yes	Yes	Yes
For furniture making	No	Yes	Yes	Yes	Yes
For furniture making	Yes	Yes	No	Yes	Yes
For construction	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	No
Cooking and firewood consumption	No	Yes	Yes	No	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	No
Cooking and firewood consumption	Yes	Yes	No	No	No
Cooking and firewood consumption	Yes	Yes	Yes	Yes	No
Cooking and firewood consumption	Yes	No	Yes	Yes	Yes

Continue……

In your opinion, which activityis consuming large amount of forest wood or resources in your area?	Do anyone from your surrounding have furniture	Is there any constructionof roads in your area?	Is there any construction work done in your area after 2010?	Do you think construction of more houses cause	Have trees been planted in your area?
Cooking and firewood consumption	Yes	No	No	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	No	Yes	Yes
For selling	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	No	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	Yes
For furniture making	Yes	Yes	No	Yes	Yes
For furniture making	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	Yes	No	Yes	No
For selling	No	No	No	Yes	No
Cooking and firewood consumption	No	No	No	Yes	No

Continue……

In your opinion, which activityis consuming large amount of forest wood or resources in your area?	Do anyone from your surrounding have furniture	Is there any constructionof roads in your area?	Is there any construction work done in your area after 2010?	Do you think construction of more houses cause	Have trees been planted in your area?
Cooking and firewood consumption	No	No	No	Yes	Yes
For construction	No	No	No	Yes	No
For furniture making	Yes	Yes	Yes	Yes	Yes
For construction	Yes	Yes	Yes	Yes	Yes
For selling	Yes	Yes	Yes	Yes	Yes
For construction	Yes	Yes	Yes	Yes	Yes
For construction	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	Yes	Yes	Yes
Cooking and firewood consumption	Yes	No	Yes	Yes	Yes
For furniture making	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	No	Yes	No
Cooking and firewood consumption	No	Yes	Yes	Yes	Yes
For construction	No	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	No	Yes	No
Cooking and firewood consumption	No	No	No	Yes	No

Continue……

In your opinion, which activityis consuming large amount of forest wood or resources in your area?	Do anyone from your surrounding have furniture	Is there any constructionof roads in your area?	Is there any construction work done in your area after 2010?	Do you think construction of more houses cause	Have trees been planted in your area?
Cooking and firewood consumption	No	No	Yes	Yes	Yes
Cooking and firewood consumption	No	Yes	Yes	Yes	Yes
For selling	No	Yes	Yes	Yes	Yes
For construction	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	No	Yes	No
Cooking and firewood consumption	No	No	No	No	No
For selling	No	No	No	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
For furniture making	Yes	Yes	Yes	No	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
For furniture making	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	No
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes

Continue……

In your opinion, which activityis consuming large amount of forest wood or resources in your area?	Do anyone from your surrounding have furniture	Is there any constructionof roads in your area?	Is there any construction work done in your area after 2010?	Do you think construction of more houses cause	Have trees been planted in your area?
Cooking and firewood consumption	Yes	Yes	No	Yes	No
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	No	Yes	Yes
Cooking and firewood consumption	No	No	No	Yes	No
For furniture making	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	No	No	Yes	No
Cooking and firewood consumption	Yes	Yes	Yes	Yes	No
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	Yes	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	Yes	Yes	Yes	Yes
Cooking and firewood consumption	No	Yes	Yes	Yes	No
For furniture making	Yes	Yes	Yes	Yes	No