ASSESSMENT OF CARBON STOCK AND CLIMATE WARMING IMPACTS ON SOME REGULATORY SERVICES OF HAYAT-UL-MIR FOREST, SOAN VALLEY, PAKISTAN

GUL ZAREEN GHAFOOR

REGISTRATION NO. 2015-GCUL-PhD-ENVS-26

SUSTAINABLE DEVELOPMENT STUDY CENTER

GOVERNMENT COLLEGE UNIVERSITY

LAHORE

ASSESSMENT OF CARBON STOCK AND CLIMATE WARMING IMPACTS ON SOME REGULATORY SERVICES OF HAYAT-UL-MIR FOREST, SOAN VALLEY, PAKISTAN

SUBMITTED TO THE GOVERNMENT COLLEGE UNIVERSITY LAHORE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF

DOCTOR OF PHILOSOPHY

IN

ENVIRONMENTAL SCIENCE

BY

GUL ZAREEN GHAFOOR

REGISTRATION NO. 2015-GCUL-PhD-ENVS-26

SUSTAINABLE DEVELOPMENT STUDY CENTER

GOVERNMENT COLLEGE UNIVERSITY

LAHORE

DECLARATION

I, **Gul Zareen Ghafoor**, Registration No. **2015-GCUL-PhD-ENVS-26**, student of Ph. D. in the subject of Environmental Science, session 2015-2018 hereby declare that the matter printed in this thesis titled, *"Assessment of carbon stock and climate warming impacts on some regulatory services of Hayat-ul-Mir Forest, Soan Valley, Pakistan"* is my own work and has not been printed, published and submitted as research work, thesis or publication in any form in any University, Research Institution etc, within or outside of Pakistan.

30-04-2021

Date

Signature of Deponent

PLAGIARISM UNDERTAKING

I, **Ms. Gul Zareen Ghafoor**, Registration No. **2015-GCUL-PhD-ENVS-26**, solemnly declare that the research work presented in the thesis titled *"Assessment of carbon stock and climate warming impacts on some regulatory services of Hayat-ul-Mir Forest, Soan Valley, Pakistan"* is solely my research work, with no significant contribution from any other person. Any contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero-tolerance policy of HEC and Government College University, Lahore towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference has been properly referred/cited.

I understand that if I am found guilty of any formal plagiarism in the above titled thesis, even after the award of Ph. D. degree, the University reserves the right to withdraw my Ph. D. degree and HEC/University has the right to publish my name on HEC/University website, in the list of culprits of plagiarism.

30-04-2021

Date

Signature of Deponent

RESEARCH COMPLETION CERTIFICATE

This is to certify that the research work contained in this thesis titled, *"Assessment of carbon stock and climate warming impacts on some regulatory services of Hayat-ul-Mir Forest, Soan Valley, Pakistan"* has been carried out and completed by **Ms. Gul Zareen Ghafoor**, Registration No. **2015-GCUL-PhD-ENVS-26**, under my supervision during her Ph. D. studies in the subject of Environmental Science.

Dated: 30-04-2021

Prof. Dr. Faiza Sharif
Supervisor
Sustainable Development Study Center
GC University, Lahore

Submitted through

Prof. Dr. Faiza Sharif
Director
Sustainable Development Study Center
GC University, Lahore

Controller of Examinations
GC University, Lahore

CERTIFICATE OF APPROVAL

It is certified that research work contained in this thesis titled *"Assessment of carbon stock and climate warming impacts on some regulatory services of Hayat-ul-Mir Forest, Soan Valley, Pakistan"* was conducted by **Ms. Gul Zareen Ghafoor**, Registration No. **2015-GCUL-PhD-ENV-26** under the supervision of **Dr. Faiza Sharif**.

It has been evaluated and the quantum and quality of the work contained in this thesis is found to be adequate for the award of degree of Doctor of Philosophy in Environmental Science.

Board of Examiners for viva voce	
External Examiner Name: Dr. Abdul Wahid Designation: Professor Office address: Department of Environmental Science, Bahauddin Zakariya University , Multan	Signature:
External Examiner Name: Dr. Azra Yasmin Designation: Professor Office address: Department of Environmental Science, Fatima Jinnah Women University, Rawalpindi	Signature:
Internal Examiner (Supervisor) Name: Dr. Faiza Sharif Designation: Professor Office address: Sustainable Development Study Centre, Government College University, Lahore	Signature:
Convener Name: Dr. Faiza Sharif Designation: Professor/Director Office address: Sustainable Development Study Centre, Government College University, Lahore	Signature:

ACKNOWLEDGEMENTS

All praises be to Allah Almighty for guiding me to the path of knowledge and wisdom. And all respects are for His last Prophet Hazrat Muhammad (SAW) who is the utmost educator for the mankind.

I would like to express my sincere gratitude to my supervisor, **Prof. Dr. Faiza Sharif**, Director, Sustainable Development Study Center, GC University, Lahore, for her continuous support during my Ph.D studies. Her invaluable help of constructive comments and suggestions during the course of study have contributed to the success of this work. I am indebted for her expertise, guidance, support and constant encouragement in accomplishing this work.

I extend my thanks to the **Vice Chancellor**, GC University Lahore for allocating research fund to purchase the chemicals required in this study. I am also thankful to the **Higher Education Commission of Pakistan** for providing funds (Project No. 3867) to conduct this research.

I express my gratitude to **Prof. Dr. Amin U Khan**, Distinguished Professor, Sustainable Development Study Center, GC University Lahore and **Dr. Zafar Siddiq**, Assistant Professor, Department of Botany, GC University Lahore for facilitating me in my experimental work at Botanic Garden of GC University Lahore. I am grateful to **Prof. Dr. Ali Iqtadar Mirza** and **Dr. Shakeel Mahmood**, Associate Professor/Chairman, Department of Geography, GC University Lahore for the guidance they provided for the spatial analyses of data.

I am grateful to **Mr. Aman Ullah Khan Awan** and **Mr. Mehboob**, officials from the Forest Department of Naushehra, District Khushab and the HEC project team members **Afsheen**, **Humayun** and **Shehzad** for helping me in the field survey. I owe my thanks to my colleagues **Mr. Muhammad Umar Hayyat** and **Dr. Laila Shahzad**, Assistant Professor at Sustainable Development Study Center for their moral support during tough times.

I pay tribute to my parents, whose guidance and prayers have always been a source of encouragement to me. I am also very thankful to my siblings especially **Dr. Memuna Ghafoor Shahid** and **Muhammad Zubair** for their support and motivation which made me able to complete this work.

Gul Zareen Ghafoor

TABLE OF CONTENTS

The Art of writing only for samples use

The Art of writing only for samples use

The Art of writing only for samples use

LIST OF TABLES

LIST OF FIGURES

LIST OF ANNEXURES

The Art of writing only for samples use

LIST OF ABBREVIATIONS/SYMBOLS AND ACRONYMS

Abbreviation/ Symbols	Acronyms
AFOLU	Agriculture, Forestry and Other Land uses
AGB	Aboveground Biomass
AIC	Akaike Information Criteria
ANOVA	Analysis of Variance
BAU	Business As Usual
BD	Basic Density
BEFs	Biomass Expansion Factors
BGB	Belowground Biomass
BIC	Beysian Information Criteria
CA	Cellular Automata
CCT	Carbon Calculation Tool
CLE	Crown Light Exposure
CO_2	Carbon Dioxide
COLE	Carbon OnLine Estimator
CS	Carbon Stock
CTCC	Tree Carbon Calculator
CUFR	Center for Urban Forestry Research
DBH	Diameter at Breast Height
FAO	Food and Agriculture Organization
FF	Form Factor
GHG	Greenhouse Gas

The Art of writing only for samples use

HM	Hayat-ul-Mir
Ht	Tree Height
IDW	Inverse Distance Weighted
InVEST	Integrated Valuation of Environmental Services and Tradeoffs
IPCC	Intergovernmental Panel on Climate Change
IVI	Importance Value Index
LiDAR	Light Detection and Ranging
LMR	Leaf Mass Ratio
LOI	Loss On Ignition Method
LULC	Land Use Land Cover
M	Soil Moisture
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
NPV	Net Present Value
OTCs	Open Top Chambers
RCP	Representative Concentration Pathway
REDD	Reducing Emissions from Deforestation and forest Degradation
REDD+	Reducing Emissions From Deforestation, Forest Degradation, Conservation, Enhancement and Sustainable Management
RMR	Root Mass Ratio
RMSE	Root Mean Square Error
RSR	Root to Shoot Ratio
SMR	Stem Mass Ratio
SOC	Soil Organic Carbon
SPSS	Statistical Package for Social Sciences
SR	Sequestration Rate
T	Temperature

The Art of writing only for samples use

TB	Total biomass
TBC	Total Biomass Carbon
TOC	Total Organic Carbon
UFORE	Urban FORest Effects
UNFCCC	United Nations Framework Convention on Climate Change
USDA	United States Department of Agriculture
WD	Wood Density

ABSTRACT

Global forests store 2.4 GtC/yr but climate warming and increase in precipitation can reduce their productivity and carbon sequestration potential. This study was designed to assess the current carbon stock and impact of predicted climatic warming and increase in precipitation on regulatory ecosystem services of the Hayat-ul-Mir (HM) subtropical scrub reserve forest, Soan Valley Pakistan. In the HM forest, tree dendrometric measurements of *Acacia modesta* and *Olea ferruginea* were taken in 47 survey plots (0.04 ha) and soil and leaf litter samples were collected from sub-plots of $1m^2$ to assess tree and forest floor carbon. The robustness of existing generic pantropical biomass allometric model of Chave et al. (2014) and i-Tree Eco tool was evaluated against local species specific volume allometric models. The satellite imagery was processed to assess spatio-temporal changes in the tree density of the HM forest during 2007, 2013 and 2019. The simulation for future land cover (year 2030) was done through CA-Markov model under business as usual scenario. The spatial land cover data of 2019 and 2030 and carbon pools data was processed in Integrated Valuation of Environmental Services and Tradeoffs (InVEST) carbon model to assess future carbon storage, sequestration and monetary benefits of the HM forest. The decomposition dynamics of mixed species leaf litter was investigated in the field (360 days) under ambient conditions. The short term effect (90 days) of predicted warming and (+2.3ºC and +4.5ºC) and increase in soil moisture ($M_{20\%}$) was investigated on decomposition of leaf litter in the laboratory microcosms. The seeds and seedlings of *A. modesta* and *O. ferruginea* were exposed to similar warming and soil moisture conditions in a plant growth chamber to assess changes in species growth rate and carbon storage potential.

Results showed that the HM forest stored 18.6 Mg/ha and 3.6 Mg/ha carbon in the tree biomass and in forest floor (soil and leaf litter) respectively. No significant difference was observed in the biomass carbon estimates (Mg/ha) made with local (8.53) and pantropical (8.68) models for *A. modesta*. The difference in the estimates for *O. ferruginea* (10.92, 11.91 and 11.87 for local allometric, pantropical model and i-Tree Eco, respectively) also remained insignificant. All allometric models fitted data well ($p < 0.001$). However, the pantropical model incorporating three biophysical variables better predicted biomass and was found more robust for both species. The

results revealed that in the absence of local models, the pantropical model can provide better biomass estimates for deciduous and evergreen subtropical species to report carbon stock. The land cover analysis showed increase in the tree density of *A. modesta* and *O. ferruginea* during baseline (2007-2019) and predicted (2030) time period. It is also expected that the total carbon stock of HM forest would increase from 23912 Mg (current) to 24024 Mg in future (2030) sequestering 112 Mg of carbon with net present value of $4112. The field decomposition of leaf litter was observed with ~48% of residual weight and 12% remaining carbon with gradually decreasing decay rate over time. Incubation time significantly affected decomposition rate but the effect of elevation remained insignificant although carbon and nitrogen mineralization was low at higher elevations ($E_{850\text{-}1020\ m}$) indicating their potential for long term carbon storage. Warming accelerated the pace of decomposition reducing litter half life by 77 days. Nitrogen and carbon mineralization was increased by 20% and 45% under interactive effect of warming and higher moisture ($M_{20\%}$) availability. There was a 40% increase in the rate of soil CO_2 efflux representing decrease in soil carbon accumulation. Seed germination was completely inhibited under warming (+4.5ºC), however only few seeds (50%) of *A. modesta* germinated and survived (67%) at +2.3ºC warming and $M_{20\%}$. Warming (+4.5ºC) induced detrimental effects on both species. Warming of +2.3ºC and $M_{20\%}$ was beneficial for *O. ferruginea* and increased its overall growth and biomass carbon accumulation (4.3 g) compared to control (3.2 g). However *A. modesta* only grew better under ambient condition. These findings suggest that although HM forest is currently storing 22.3 Mg/ha carbon but warm and wetter future will reduce its soil carbon stock. It might also induce shifts in the productivity and provision of ecosystem services by co-occurring species of the HM forest. Future rise of 2.3ºC in mean temperature could be ecologically significant to cause changes in the ecosystem structure by favoring the growth of *O. ferruginea* and restricting the growth of *A. modesta*. The study recommends taking proactive measures to enhance the carbon sequestration potential by increasing tree density and restricting anthropogenic activities in the forest.

Chapter 1

INTRODUCTION

Climate change has become one of the greatest global concerns in recent times. The uncontrolled urban and industrial expansions leading to fossil fuel burning have caused a significant increase in the global Greenhouse Gas (GHG) emissions (Abeydeera et al., 2019). The current concentration of global atmospheric CO_2 emissions has already reached 409 ppm and world is progressing to reduce it from reaching to a dangerous level of 495 ppm by the end of this century (Vachnadze et al., 2018; Olivier & Peters, 2020). It has been projected that unchecked increase in GHG emissions will raise global temperature from current 0.85ºC (observed) up to 4ºC (projected) by year 2100 (Szulejko et al., 2017; World Meteorological Organization, 2019). This warming trend will increase the incidence of natural disasters such as heat waves, drought, storms, floods, sea level rise and would also disturb the ecological balance (Aye & Edoja, 2017; Perera, 2018; Abeydeera et al., 2019; Malhi et al., 2020). The scientific community is striving to find ways to reduce GHG emissions to mitigate the impacts of climate change (Abeydeera et al., 2019).

The best way to tackle this problem is by capturing the CO_2 and storing it in a carbon pool during a process called carbon sequestration. There are four global carbon pools i.e. oceanic (38,000 PgC), geologic (5,000 PgC), terrestrial (3,060 PgC) and atmospheric (760 PgC) pools. Among these, the terrestrial carbon pool contributes significantly in storing carbon in the vegetation (560 PgC) and soil (2,500 PgC) (Issa et al., 2020). These terrestrial ecosystems have been reported to remove 30% of the anthropogenic CO_2 emissions during 2008 to 2017 (Le Quéré et al., 2018; Zeng et al., 2020).

Forests cover globally 4.06 billion hectares or ~31% of the total land surface area and store 2.4 GtC/yr (Pan et al., 2011; Ni et al., 2016; FAO, 2020). Geographically, 55% of this carbon is stored in the tropical and subtropical forests whereas boreal and temperate forests account for 32% and 14% of their share respectively (Pan et al., 2011). Forest ecosystems are considered as major carbon sinks and mainly store 42% of carbon in the live biomass (above and belowground), 44% in the soil, 8% in the deadwood and 5% in the leaf litter (Pan et al., 2011; Sun & Liu, 2020).

Considering the huge potential of forests in combating climate change, quantification of forest carbon reserves has become an important requirement for countries signatory to REDD+ initiative (Reducing Emissions from Deforestation, Forest Degradation, conservation, enhancement and sustainable forest management). The REDD+ initiative, launched in countries with high rates of deforestation and forest degradation, provide them with a framework of carbon credits as incentives for enhancing their forest cover and reducing GHG (Greenhouse gas) emissions (Bayrak & Marafa, 2016; McCall et al., 2016).

The productivity and rate of carbon sequestration of these terrestrial sinks is mainly defined by climatic factors which if disturbed, affect ecological processes such as nutrient cycling, species growth rate and carbon storage potential (Li et al., 2017; Wu et al., 2019). The change in the global CO_2 concentrations, climate warming and precipitation changes cause tree species to shift their range towards higher latitudes and altitudes (Fei et al., 2017). The net primary productivity (NPP) of the global forests is not saturated at the present atmospheric CO_2 concentration, but higher future CO_2 levels might induce fertilization effect (Lal, 2008; Sun & Liu, 2020). However, recent changes in temperature and precipitation have increased the vulnerability of subtropical forests to climate change (Sun & Liu, 2020; Wu et al., 2020).

The elevated levels of CO_2 concentration in the future would increase carbon storage in above and belowground plant components, but it might accelerate the metabolic activity of soil microflora promoting the soil carbon and nitrogen losses (Cha et al., 2017; Rai et al., 2020; Zou et al., 2020; Chen et al., 2021). The elevated CO_2 concentration can also increase leaf biomass due to higher carbon assimilation rate but might reduce stem elongation in some tree species (Gray & Brady, 2016; Thompson et al., 2017). Elevated temperature increases soil CO_2 efflux associated with higher decomposition rates and also promotes above and belowground carbon sequestration in some species while decrease it in others with reduced photosynthetic rate (Gray & Brady, 2016; Li et al., 2017; Gustafson et al., 2017; Prieto et al., 2019; Stuble et al., 2019; Li et al., 2020; Wu et al., 2020). Reduction in overall growth and root biomass of tree species has been observed in response to drought but increase in soil carbon loss due to higher precipitation rates (Gray & Brady, 2016; Dannenberg et al., 2019). It has been observed that warming coupled with elevated CO_2 levels promote soil

carbon losses and evapotranspiration resulting in limited plant growth if not compensated with precipitation (Stuble et al., 2019; Wu et al., 2020).

Pakistan has 6.7% of its land area covered by forests which is much lower than the world average of 25%. This low forest area coverage makes Pakistan rank at 113th place among the list of 140 countries with forest covers (Ilyas et al., 2012; Government of Pakistan, 2015; FAO, 2019). Current study was conducted on Hayat-ul-Mir Scrub Dry Subtropical Broadleaved forest located in the Soan Valley of Salt Range in the district Khushab of Pakistan. The scrub forests in Pakistan cover an area of 1.3 Mha (0.3 Mha in Punjab alone) (Government of Pakistan, 2015). These forests extend in the foothills and lower slopes of the Himalayas, Kala Chitta, Suleman and Salt ranges storing ~27.8 Mg/ha carbon (Nizami, 2012). At suitable elevations the forest is found distributed throughout the country and merges upward with sub-tropical pine and temperate forest and downward with tropical thorn forest (Parker, 1915; Champion et al., 1965; Sheikh, 1993; Government of Pakistan, 2015). The local population relies on this forest for its medicinal importance and for fodder, timber and fuelwood harvesting (Khan & Ahmad, 2015).

The scrub dry subtropical broadleaved forest is characterized with low branchy trees with varying tree density and a fair cover of shrubs depending on the aridity of the soil. The vegetation type of these forests comprise of both deciduous and evergreen tree species including *Olea ferruginea* Royle, *Acacia modesta* Wall, *Pistacia integerima* and *Tecoma undulata* while *Capparis aphylla*, *Dodonaea viscosa*, *Reptonia buxifola*, *Gymnosporia royleana*, *Nannorrhops ritchieana* and *Zizyphus spp*. make the shrub cover. Boulders and rocks are a common feature of these forests. The arid climate makes hot summer and cold winter with long periods of drought. Scrub forests receive erratic rainfall but generally during the months of July and August in summers and January and February in winters (Sheikh, 1993).

Salt range is a significant geological and ecological region of Pakistan spreading over a length of 150 miles and derives its name due to the presence of gigantic rock salt deposits (Ahmad et al., 2007; Sameeni, 2009). Laying in the heart of salt range is the Soan Valley which is well known for its famous saline Ramsar wetlands i.e. Khabeki and Ucchali lakes and subtropical vegetation in the reserve forests (Ahmad & Waseem, 2006; Ahmad et al., 2007). The valley has variable topography with average

The Art of writing only for samples use

height of the hills about 766 m ranging between 650 m to 1530 m covering an area of 750 km^2 (Khan et al., 2019). Sakesar is the highest peak laying at an elevation of 1527 m. The climate of the valley is BShw (Steppe hot with dry winter) as per the Koppen Gieger Classification System and receives 400 mm of annual rainfall with average temperature of 24.5^{o}C (1°C average minimum and 36°C average maximum temperature). Such a type of climate makes area hot and dry with recurrent droughts in summer and frost in winter (Ahmed, 2013; Khan et al., 2013). Both summer and winter temperatures of the valley are relatively cooler than adjoining plain areas with generally longer winter season in the valley (Ahmad et al., 2007).

Soan valley has dominant cover of subtropical vegetation in the Passlian, Suraki, Kuradhi, Khura, Keri, Parr, Jehlar, Sakesar and Hayat-ul-Mir (HM) scrub reserve forests and is surrounded by number of small villages. The rural communities of the valley exploit forest area for the cultivation of common crops i.e. cauliflower and tomato leading to land use changes and reduction in the forest cover. The valley has also been documented with high rates of deforestation and encroachments by human settlements at some locations (Ahmad & Waseem, 2006; Ahmad et al., 2008).

1.1. Study Area

This study was conducted in Hayat-ul-Mir (HM) scrub dry subtropical broadleaved forest. It is a reserve forest located at 32.54^o N and 72.31^o E covering an area of 1652 ha in the Soan Valley, District Khushab of Punjab province, Pakistan. The elevation in the forest varies between 620 m to 1020 m. The forest is classified as arid and receives annual precipitation of 600 mm which falls mostly during the monsoon (July to September). The average annual temperature of 24°C (min. 1°C in January and max. 36°C in June) and erratic rainfall pattern makes the area hot and dry with frequent droughts during the summer and frost in winter (Ahmed, 2013; Khan et al., 2013).

The forest has a dominant cover of subtropical broadleaved bi-climax community of *Acacia modesta* and *Olea ferruginea*. The thorny deciduous tree of *A. modesta* (or Phulai) is usually 3 to 9 m tall. It is drought resistant and is able to grow under semi-arid and sub-humid climate within a temperature range of –5°C to 40°C. It is known for its fuelwood, gum and medicinal values (Sheikh, 1993; Sarwar, 2016). The

The Art of writing only for samples use

evergreen tree of *O. ferruginea* (Indian Olive or Kahu) attains height up to 9 to 12 m. It grows well in the arid to semi-arid and sub-humid subtropical and temperate climate within –10°C to 40°C temperature range. It is a source of oil and fruit and is known for its antimicrobial properties (Sheikh, 1993; Mehmood and Murtaza, 2018). A rich understorey shrub cover in the forest is made by *Dodonaea viscosa* L., *Justicia adhatoda* L., *Buxus semipervirens* L. and *Maytenus royleanus* Wall (Ahmed, 2013; Khan et al., 2019).

Before the implementation of the Punjab Forest (Amendment) Act (2010) and lack of clearly defined property rights, the scrub forests suffered extensive degradation. But bulk of the intact scrub forests is now under government control (Khan et al., 2013). The implementation of the Punjab Forest (Amendment) Act (2010) defined rights and penalties restricting any anthropogenic activities related to mining, cultivation and timber harvesting (Government of Punjab, 2010). In the past locals were given rights to harvest colonizer plant (*Dodonaea viscosa*) which led to illegal removal of native tree species. This had set ground for exotic invasive tree species i.e. *Prosopis juliflora* which is competing native plant species affecting ecosystem structure and function. The area is surrounded by small towns i.e. Ararra in the east, Khura in the west, Nalli in the south and Kalial and Bayyakh towns and vast tracts of agricultural fields in the north (Figure 1.1).

The Art of writing only for samples use

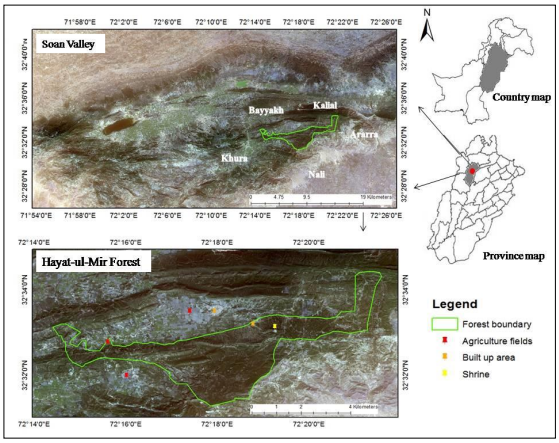

Figure 1.1: Map of study area showing the location of Hayat-ul-Mir Reserve Forest.

This study was designed to investigate the current carbon stock and future carbon storage potential of HM forest under the impact of predicted climatic warming. Along with the socio-economic drivers of ecosystem degradation, the subtropical scrub forest in Pakistan is also facing threats of climate change. Over a time span of 100 years about 75% cover of the scrub forests in Pakistan has been lost and degraded (Khan et al., 2019). The historical 0.6 – 1°C rise in the mean annual temperature over the last 40 years has significantly affected natural systems in Pakistan (Chaudhry, 2017). Scrub forest in the Soan valley has been reported with considerably low precipitation (20 in.) over the last decade which resulted in reduction in the water table of the valley. Frequent and long periods of drought have also severely affected water availability to the forest vegetation (Ahmad et al., 2002; Ahmad et al., 2012; Bibi et al., 2014). Chaudhry (2017) citing Siddiqui et al., (1999) predicted decline in

the cover of scrub forest by 3.6% in year 2050 under 1.8ºC rise in the mean annual temperature of Pakistan.

The Intergovernmental Panel on Climate Change (IPCC) has suggested warming between 2 – 5ºC for South Asia by the end of this century and has predicted its effects to be most likely occurring on land surfaces (Cruz et al., 2007; CDKN, 2014; Chaudhry, 2017). It also suggested decline in precipitation and frequent drought events for arid regions of the country (IPCC, 2014; IPCC, 2020). The current warming trend will equally impact both socio-economic and ecological systems such as forests storing huge amounts of carbon. Any loss or degradation of forest cover means emission of bound carbon back into the atmosphere leading to the positive feedback to climate change. But to the best of knowledge no significant studies have been made in Pakistan investigating the impacts of climate change on carbon storage potential of forest ecosystems.

1.2. Study Objectives

The aim of this study was to assess the current carbon stock and impact of predicted climate warming on regulatory ecosystem services of the Hayat-ul-Mir (HM) forest. Specific objectives of the current study were to:

1. Estimate the current carbon stored in the aboveground and belowground parts of the climax community of the HM scrub forest i.e. *Acacia modesta* and *Olea ferruginea* and in the soil and dead (leaf litter) pools.
2. Check the robustness and validity of the generic pantopical biomass allometric models against local species specific harvest based allometric models to evaluate their applicability in Pakistan.
3. Assess the economic benefit and spatio-temporal distribution of tree carbon storage and sequestration service provided by the current and future land covers of the HM forest.
4. Investigate the factors affecting the rate of leaf litter decomposition, carbon and nitrogen mineralization in the field (HM forest) and in the laboratory microcosms under current (ambient) and future climate warming scenarios.

5. Assess the impacts of predicted climate warming and soil moisture on seedling emergence, survival, growth and biomass accumulation and allocation of *Acacia modesta* and *Olea ferruginea* as a measure of their carbon storage potential.

1.3. Study Organization

This study has been designed to assess the carbon storage potential of the HM forest. After this introductory chapter, a detailed review of literature is presented in Chapter 2. Chapters 3 to 6 are based on details of the field survey and laboratory experiments conducted to estimate the forest carbon stock. Figure 1.2 presents the framework of the study to estimate the current carbon stock and effects of predicted climatic warming and increase in precipitation on carbon storage potential of the HM forest. The estimation of the current carbon stored in the bi-climax community of the HM forest is based on vegetation sampling. The analysis also deals with the comparison and validation of three biomass allometric models to accurately account for the current tree carbon stock (Chapter 3). The estimation of the economic benefit and spatio-temporal distribution of the current and future carbon sequestration of the HM forest have been made using carbon pools (tree and forest floor) and spatial land cover data (Chapter 4). The future carbon sequestration potential of the HM forest has been assessed through two laboratory based experiments. The impacts of warming and increase in precipitation have been evaluated on decomposition of organic litter fractions (Experiment 1 in Chapter 5) and on species growth rate (Experiment 2 in Chapter 6) to estimate potential soil and tree carbon storage. Chapter 7 presents a detailed general discussion followed by conclusions and recommendations of this study.

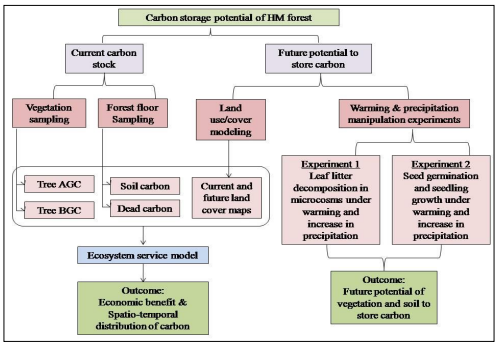

Figure 1.2: Framework of the study to estimate carbon storage potential of the HM forest.

Chapter 2

REVIEW OF LITERATURE

This chapter presents the review of existing relevant literature on assessment of ecosystem carbon storage and impact of climatic warming on regulatory ecosystem services. The chapter is organized into two main sections as follows;

- Assessment of forest carbon stock
- Anthropogenic disturbances and ecosystem carbon storage

2.1. Assessment of forest carbon stock

Anthropogenic activities leading to forest deterioration and degradation has significantly increased greenhouse gas (GHG) emissions aggravating the impacts of climate change (Abeydeera et al., 2019). Forests store huge amount of carbon in the vegetation, soil and in dead organic matter (wood and leaf litter) and mitigate the impacts of climate change. Most of this carbon is stored in the aboveground (AGB) and belowground biomass (BGB) and in soil while deadwood and leaf litter account relatively for a small proportion of the total biomass carbon (Sun & Liu, 2020). In order to qualify for incentives under REDD+ (Reducing Emissions from Deforestation, Forest Degradation, conservation, enhancement and sustainable management), it is important for signatory countries to report changes in their forest carbon stock overtime and from leakage (Yuan et al., 2016).

The countries signatory to REDD+ rely on IPCC (Intergovernmental Panel on Climate Change) default (Tier 1) approach or UNFCCC (United Nations Framework Convention on Climate Change) protocols to report their standing carbon stock (UNFCCC, 2015; McCall et al., 2016). These protocols are based on tree biometric measurements of the diameter at breast height (DBH), tree height (Ht) and wood density (WD) to calculate aboveground biomass (Njana, 2017; Kenzo et al., 2020).

A number of studies have been made on the estimation of tree biomass through remote sensing (Rodríguez-Veiga et al., 2017; Urbazaev et al., 2018; Zhang et al., 2019; Issa et al., 2020; Li et al., 2020). This method is often considered advantageous

over field measurements for its low cost and high speed of acquiring high or medium resolution optical, radar, LiDAR (Light Detection and Ranging), Landsat and Sentinel data (Bernasconi et al., 2017; Urbazaev et al., 2018; Zhang et al., 2019; Issa et al., 2020). This method is an alternative to the traditional approaches but remotely sensed measurements are often limited due to low sensitivity of sensors to AGB. The data generated must also be calibrated and validated with field based biomass estimates to ensure its accuracy (Rodríguez-Veiga et al., 2017; Gonçalves et al., 2017; Urbazaev et al., 2018). But the plot estimates obtained with indirect methods (allometric equations) may be uncertain based on the number of predictor variables and the choice of the model selected (Chen et al., 2015; Goussanou et al., 2016; Huy et al., 2016; Yuan et al., 2016; Stas et al., 2017). Gonçalves et al. (2017) investigated the uncertainties associated with the plot based estimates to assess its reliability to calibrate remotely sensed measurements. The study found 25% uncertainty in the field data resulting from spatial and temporal disagreement between remote and field measurements. Confidence in remotely sensed estimates of carbon stock can be increased by a thorough understanding of the errors associated with spatial and temporal variation in estimates.

The most accurate and direct assessment of biomass carbon stock can be done through the destructive harvest of sample vegetation. Component biomass is estimated directly from the oven dry weight of the harvested vegetation or from the volume of plant parts (xylometric estimation). The volume of the components is later converted into biomass by multiplying with wood density. The measurements of tree biometrics and biomass determined are then used to devise allometric equations to compute site/species specific aboveground biomass (Yuen et al., 2016; Zhao et al., 2019). The destructive harvest is often limited in use from the conservation perspective, its financial constraints and variable topography restricting movement of machinery in the forest (Goussanou et al., 2016; Djomo & Chimi, 2017). To tackle this issue, researchers have developed non-destructive volume and biomass allometric models which are pre-calibrated using harvest data from range of sites (Yuen et al., 2016; Stas et al., 2017; Romero et al., 2020).

The estimation of biomass carbon stock is highly sensitive to the choice of method adopted and considerable uncertainty may result due to inappropriate method

selection (Picard et al., 2015; Zhao et al., 2019). It is important to apply existing knowledge on tree allometry available in the form of volume or biomass models to improve reliability of estimates (Romero et al., 2020). Simple volume equations develop a geometrical relationship between tree biophysical/dendrometric variables such as DBH, Ht and tree form factor (FF) to compute volume. It is then multiplied with species specific wood density (WD) or biomass expansion factors (BEFs) to estimate tree biomass. However, an indirect approach to estimate AGB through simple volume models may generate uncertainties in estimates (Njana, 2017; Romero et al., 2020).

Njana (2017) compared biomass estimates from direct (destructive) and indirect volume models based on FF, BEF and WD of three mangrove species in Tanzania. In 37 transects, DBH and Ht were measured and sample trees were harvested and the fresh weight of the aboveground parts (stem, branches, twigs and leaves) was taken. Xylometric determination of the volume of the subsamples was done and two volume models were developed (based on DBH only and DBH and Ht). Direct estimation of biomass was also done based on the oven dry weight of wood samples. These estimates were then compared with indirect models using FF, BEF and WD of the mangrove species. It was reported that both harvest based volume models fitted data well while the indirect models significantly overestimated (20%) the AGB. The uncertainties associated with indirect volume models suggested their limited applicability when the development of direct models was not feasible.

Volume models constructing a simple geometrical relationship between DBH, Ht, FF and WD to estimate AGB assume that taper (or form factor) does not change with tree height, age, species and site conditions (Bronisz & Zasada, 2019; Socha et al., 2020). These volume models were originally developed by foresters, but are now less recommended and seldom used in AGB estimation due to fixed taper. These models are also limited in use in closed canopy forests where it becomes difficult to measure tree height (Larjavaara & Muller-Landau, 2013; Wang et al., 2019). In such cases models involving only DBH and those assuming allometric relationship between tree biophysical factors are usually preferred (Kenzo et al., 2020). The reliability of the allometric models depends on its validation or calibration with the AGB estimated from destructive harvest. When estimating AGB with indirect methods, it becomes

difficult to choose between the generic (multispecies) and site/species specific allometric models (Goussanou et al., 2016).

The validity of site specific and generic allometric models was assessed by fitting these equations on a dataset of 101 destructively sampled trees at Zadié in Northeastern Gabon, Africa. Out of the ten site specific allometric equations, only two models (with and without height) fitted data well. These equations were then compared with the generic pantropical allometric model of Chave et al. (2005) for moist and wet forests. Models for moist forest considerably overestimated biomass by ~40% and were not valid for Zadié. However, generic model for wet forests was found valid for that site although the climatic zone was different. The study suggested a more detailed investigation of the factors causing variations in biomass estimates among different sites to rule out uncertainties (Ngomanda et al., 2014).

Goussanou et al. (2016) developed generic and specific biomass allometric models for eighteen semi-deciduous tropical tree species in West Africa. Non destructive sampling technique was adopted and a sample of 501 trees was taken to estimate stem biomass and volume. Models based on DBH, and Ht and those with logarithmic relationship between biophysical variables had better predictive abilities. Species specific models were found more appropriate for tropical forest than generic models. Daba and Soromessa (2019) also reported higher bias in AGB estimates made with pantropical generic equation compared to species specific equations for tropical moist montane forest in Ethiopia.

Site specific equations developed after harvesting a small sample of trees from an individual forest or from a smaller site can only accurately estimate biomass of that site (Kebede & Soromessa, 2018; Zhao et al., 2019). These equations if applied outside the geographical range of its development considerably produce uncertainties in biomass estimates (Ishihara et al., 2015; Tashi et al., 2017). These site based or local equations, which may have been originally devised for a particular species or for multiple species, also have limited utility for not considering inter or intra specific differences (Ishihara et al., 2015; Correia et al., 2018). Generic allometric models have been developed to overcome the limitations associated with applicability of site or species specific equations outside the geographical region. Such equations are developed from raw dataset based on a large number of species from diverse habitats

(Chave et al., 2014). These equations may rely on single biophysical variable (DBH or Ht) or combination of the two or more variables which helps in identifying interspecific differences (Huy et al., 2016; Mukuralinda et al., 2021).

Generic allometric equations are developed for multiple species and are applicable to regions of its development. Like site specific equations, uncertainties are associated with the utility of generic equations if applied outside the geographical boundaries (Vieilledent et al., 2012). Significant work has been done on the development of generic pantropical allometric equations for multiple species in the tropical region. These models rely on a different set of biophysical variables to estimate tree biomass (Chave et al., 2005; Chave et al., 2014; Djomo et al., 2016; Mukuralinda et al., 2021).

Chave et al. (2005) developed generic pantropical allometric models to nondestructively estimate AGB of tropical moist, dry and wet forests. The allometric models were developed by compiling harvest dataset from 27 sites across the tropics in parts of America, Asia and Oceania. Different types of generic regression models were developed based on the relationship between tree DBH, Ht and WD or between DBH and WD only to estimate AGB. Tree DBH, WD, Ht and forest type were found as predictors in decreasing order of significance respectively and the models were found reliable for the AGB estimation of tropical forests.

Regional allometric models were developed for Madagascar by compiling harvest dataset of 481 trees from spiny dry and moist forests. The AGB estimates of regional allometric models were compared to those made with pantropical models of Chave et al. (2005). The pantropical models combining DBH, Ht and WD gave accurate AGB estimates with high coefficient of determination (> 83%) and the lowest bias (< 6%) compared to the regional models. The study highlighted the robustness of generic pantropical models when local or regional models are not available (Vieilledent et al., 2012).

Chave et al. (2005) misrepresented under-sampled regions in South America and also did not consider harvest dataset from Africa. Chave et al. (2014) compiled global harvest dataset from 58 sites across a diverse climatic and vegetation range in the tropics and improved allometric models of Chave et al. (2005). A single generic pantropical allometric model was found better predicting AGB of tropical forests

considering DBH, Ht and WD as predictor variables with no observable effect of environmental conditions. In cases when height data was not available, the pantropical model based on DBH, WD was found performing well to estimate tree biomass. The pantropical models were found reliable for the assessment of tree biomass in the tropical region with little bias suggesting the development of local diameter-height relationships to improve accuracy of estimates.

The species specific local, regional or generic allometric equations are constructed by developing relationship between tree biophysical variables. A model thus can either be based on a single variable i.e. DBH or Ht only model, or a combination of these including additional factors of WD, crown area, tree age or site quality which may result in variable estimates (Nam et al., 2016; Djomo & Chimi, 2017; Kebede & Soromessa, 2018; Mukuralinda et al., 2021). Inclusion of the additional covariates in DBH only model may improve biomass estimates with an overall better fit of the model (Ishihara et al., 2015; Djomo et al., 2016; Huy et al., 2016; Kebede & Soromessa, 2018).

Ishihara et al. (2015) developed generic allometric models by compiling a dataset of 102 species (1203 harvested trees) from subtropical, temperate and boreal forests in Japan. The generic models provided better AGB estimates than local models applied outside the site of their development. Different sets of explanatory variables were considered in the generic equations and those considering species specific WD best predicted AGB. Inclusion of functional type was found better predicting root, leaf and branch biomass. Among the biophysical variables, generic equations including both DBH and tree Ht were found performing better in estimating stem biomass.

Djomo et al. (2016) developed site specific allometric models for African forests for which previously no models were available. Dataset based on 896 trees from five tropical African countries i.e. Madagascar, DR Congo, Cameron, Gabon and Ghana was compiled. Multispecies allometric equations were developed for wet, moist and dry forest ecosystems. Equations combining DBH and Ht were found better predicting biomass. Inclusion of WD in allometric equations improved the biomass estimates. When compared to the pantropical and other general allometric equations, the site specific equations (dry, moist and wet) had better predictive capability. The study suggested relative significance of inclusion of biophysical variables in allometric

models and promoted use of site specific equations, if available, to estimate tree biomass.

Huy et al. (2016) destructively sampled 110 trees belonging to 41 species in the South Central Coastal region of Viet Nam. Different power models were constructed and evaluated based on their goodness of fit statistics to estimate AGB. The power models combining DBH, Ht, WD and crown area had lowest AIC (Akaike Information Criteria) and RMSE (Root Mean Square Error), mean percent error and high coefficient of determination (R^2) than single variable models. Inclusion of crown area significantly improved accuracy of the estimates. The local DBH only model produced more reliable estimates when compared to the generic pantropical model using up to three covariates.

Vargas-Larreta et al. (2017) developed allometric equations after compiling a harvest dataset of 1336 pine and oak trees in Northwestern Mexico. The fitted equations showed variance of 91%, 82%, 83% and 76% in wood, bark, branch and foliage biomass respectively while 93% variance was found in total observed AGB. Addition of tree height in DBH only models significantly improved individual component and total biomass. In comparison to the existing models for the site, the equations developed had higher predictive power to estimate AGB.

Kebede and Soromessa (2018) developed species specific allometric models to estimate AGB of *Olea europea* L. subsp. *cuspidata* through semi-destructive technique in Mana Angetu Forest in Ethiopia. Out of the seven allometric equations developed, three were based on single covariate i.e. DBH/Ht/WD and four in combination. The allometric models based on combination of covariates were good fit and had high value of R^2. adj., lower standard residual error and AIC than single variable models. Models combining two or three covariates showed significant relationship ($p < 0.000$) of dendrometric variables with AGB, but when evaluated individually, Ht and WD were not significantly correlated with biomass. The study rejected single variable species specific allometric equations, while combined variable models were found robust for carbon stock assessment of *O. europea* L. subsp. *cuspidata*.

Apart from the indirect estimation of tree biomass using allometric models, some software tools also provide the same purpose. Among these U.S. Forest Carbon Calculation Tool (CCT), Carbon OnLine Estimator (COLE), Center for Urban Forestry Research (CUFR) Tree Carbon Calculator (CTCC) and i-Tree tools are some of the tools that can be used to estimate carbon stock of natural and urban forests (Aguaron & McPherson, 2012; Nowak et al., 2013; Russo et al., 2014; Song et al., 2020). i-Tree tools were developed by United States Department of Agriculture (USDA) Forest Service and Cooperators. There are many web and desktop based tools such as i-Tree streets, i-Tree Eco, i-Tree landscape, i-Tree Canopy and others to quantify magnitude and monetary value of various ecosystem services (Nowak et al., 2013). i-Tree Eco is derived from UFORE (Urban FORest Effects) model designed by USDA and quantifies the magnitude of ecosystem services along with tree and plot scale estimates of carbon in urban and natural forests. This tool has widely been used in United States and European countries (Auguaron & McPherson 2012; Nowak et al., 2013; Russo et al., 2014; Boukili et al., 2017). The allometric equations in tool are based on North American tree species. However, the tool can also be used in other regions as it relies on meteorological observations of the site and species/genus/family specific allometric equations. In cases if specific equations are not available, the tool computes tree dry weight biomass and carbon through average of hardwood/conifer equations using either DBH, a combination of DBH and Ht or Ht of the tree and crown characteristics (Nowak et al., 2013).

Like allometric equations, various tools used to compute tree dry weight biomass may result in variable estimates. Aguaron and McPherson (2012) compared i-Tree Eco, i-Tree Streets, CUFR CTCC and urban general equations (UGEs) to explain variability in CO_2 estimates associated with the choice of method adopted in Sacramento's urban forest. For a sample of 640 trees, i-Tree Streets and CUFR CTCC produced the highest carbon storage estimates, followed by UGEs and lowest by i-Tree Eco. The i-Tree Eco produced the lowest estimates as it applied a correction factor of 0.80 to the open grown trees in the urban forest. The estimates were also low because i-Tree Eco considered tree health and mortality as factors determining tree carbon storage.

A subsample of trees was taken in the urban forest of Bolzano, Italy to assess carbon storage through European city specific allometric equations, i-Tree Eco and CUFR

CTCC. In comparison to the European models, i-Tree Eco produced the lowest estimates while CUFR CTCC produced highest carbon storage estimates. The estimates varied because of difference in the statistical form of the models and also because i-Tree Eco considered a reduction factor of 0.80 in computing tree biomass (Russo et al., 2014).

Being signatory to REDD+, Pakistan needs to accurately report its GHG emissions and forest carbon stock (Nizami, 2014). At present, very little work has been done on assessment of forest carbon reserves in Pakistan and most of these assessments have been made using simple geometric volume models (Nizami et al., 2009; Nizami, 2012; Gulzar et al., 2014; Shaheen et al., 2016). Most of the forest types in Pakistan are present in the temperate and subtropical regions for which no generic, regional or harvest based species/site specific biomass allometric models are available. This leads to the use of generic pantropical models or simple volume models which may result in uncertainties in estimates.

Present study was designed to estimate current carbon stock and impact of climate warming on some regulatory services of the Hayat-ul-Mir Scrub Subtropical forest in the Soan Valley of Pakistan. This subtropical scrub forest comprises of the bi-climax community of *Olea ferruginea* and *Acacia modesta* for which no biomass allometric models (generic or specific) are available. Only one study in Pakistan (Abbas et al., 2011) developed biomass allometric models for the individual components of *Olea ferruginea* after harvesting only five sample trees of exploitable diameter (24 cm). The harvested trees were separated into components, dried and volume of each component (twigs and leaves) was determined. The biomass of stem and branches was computed after multiplying volume with WD and 20% of the total biomass was taken as root biomass. From this data regression based allometric models were developed to estimate tree component biomass relying on single variable i.e. DBH.

Nizami (2014) developed regression relationships between non destructive estimates of stem biomass and DBH reported by Abbas et al. (2011) and Nizami (2012) and compiled DBH allometric models for *A. modesta* and *O. ferruginea*. Single variable models (DBH only) have been reported with low prediction capabilities in literature and should be selected with caution (Ishihara et al., 2015; Vargas-Larreta et al., 2017; Kebede & Soromessa 2018; Mukuralinda et al., 2021). The models developed by

Abbas et al. (2011) may not be reliable to estimate tree biomass for harvesting only five sample trees, all belonging to DBH of 24 cm. Roxburgh et al. (2015) stressed the importance of a representative sample of harvested trees belonging to various DBH classes to accurately predict biomass from the allometric models. For a stem diameter model to perform best in predicting AGB, approximately 17 – 95 individuals across DBH size classes must be harvested to keep a standard deviation within 5% of the mean of estimates. This review highlights the need to evaluate the robustness and applicability of existing generic models against local harvest based models to accurately report carbon stock of the subtropical forests in Pakistan.

Forests remove carbon from the atmosphere and store it in their biomass thereby playing integral role in global carbon budget (Viera & Rodriguez-Soalleiro, 2019). The current carbon stock of the global forests is 861 ± 66 PgC and tropical and subtropical forests make a major contribution (471 ± 93 PgC) to this carbon budget. Being signatory to UNFCCC the countries have an obligation to report GHG emissions and changes in their carbon stock in AFOLU sector (Agriculture, Forestry and Other Land uses) (Nizami, 2014). This requires not only the quantification of standing (above and belowground) and lying (deadwood) biomass but also of soil and litter carbon stock.

A number of studies have been conducted on estimation of carbon stock of the subtropical forests. The carbon sequestration potential of the *Cryptomeria japonica* dominated subtropical mountain forests in Taiwan has been estimated to be 274,571 tons (Chang et al., 2017). Dai et al., (2018) documented 71.2 Mg/ha of carbon stored in the topsoil of subtropical forest in Southern China. Viera and Rodríguez-Soalleiro (2019) reported 118 Mg/ha, 30.6 Mg/ha, 8.34 Mg/ha and 99.7 Mg/ha of the carbon stored in the aboveground, belowground, litter and soil respectively in the subtropical forest in Southern Brazil with a dominant cover of *Eucalyptus spp*. Zhang et al. (2019) reported 26.2 Mg/ha carbon stored in the Jiangxi subtropical forests in China. In the Panchase conservation area in Nepal, the subtropical oak forests stored 127.6 Mg/ha carbon in the live biomass (above, belowground) and in the litter fractions (Poudel et al., 2020). A synthesis of 100 studies from the subtropical forests in the Indian Himalayan region documented 138.5 Mg/ha carbon stored in the live biomass (Ahirwal et al., 2021).

In Pakistan, the native subtropical pine forest in Ghoragali and Lehterar stored 126 Mg/ha and 99 Mg/ha of carbon (Nizami, 2009). Nizami (2012) reported 31.18 Mg/ha and 24.36 Mg/ha carbon stored in the Kherimurat and Sohawa subtropical broadleaved scrub forests in Pakistan. Shaheen et al. (2016) documented 151.38 Mg/ha carbon in the live biomass and 34.89 Mg/ha carbon stored in the soil of the subtropical broadleaved forest in the Kashmir Himalayas. The subtropical broadleaved evergreen forest dominated by *Olea ferruginea* in the Malakand region stored 49.5 Mg/ha carbon (Ali et al., 2019). Khan et al. (2020) reported 145 Mg/ha AGB and 72 Mg/ha carbon stored in the subtropical pine forest in Azad Kashmir, Pakistan. Siddiq et al. (2021) reported 49.82 Mg/ha carbon stored (80% as AGB and 20% as BGB) in the Hayat-ul-Mir subtropical scrub forest in Pakistan.

2.2. Anthropogenic disturbances and ecosystem carbon storage

Forests supply diverse ecosystem services and are directly affected by land use land cover changes (LULC) induced by socioeconomic drivers (Trisurat et al., 2019). Other factors such as rising global greenhouse gas (GHG) concentrations also play their pivotal role in changing land cover by favoring the growth of one species and restricting the growth of others (Rodriguez-Echeverry et al., 2018). The considerable loss of tropical forests (34%) released 12.5% of the total anthropogenic carbon emissions and reduced the economic value of carbon sequestration by 29% during 1997 to 2011 (Costanza et al., 2014).

LULC changes are related to land management practices which may deplete or increase ecosystem carbon storage and sequestration depending on the type and extent of land cover converted (Liang et al., 2017; Sil et al., 2017). For instance, conversion of forest to agriculture land increases food supply, but reduces the carbon sequestration potential (Xu et al., 2016). Therefore assessment of changes in forest cover and its service of carbon sequestration are crucial for appropriate land use planning, and to gain maximum benefits from conservation efforts. In this regard, integrated modeling approaches are now widely used to simulate and predict the impact of LULC changes on forest carbon storage and sequestration (Sil et al., 2017).

Integrated Valuation of Environmental Services and Tradeoffs (InVEST) model, developed by Natural Capital Project, is one of the most widely used approach to

determine the magnitude and spatial distribution of multiple ecosystem services (Sil et al., 2017). InVEST carbon model helps in mapping and quantifying the current carbon stock. But it is limited in calculating monetary benefits and future carbon sequestration due to lack of an in-built simulation module. Therefore, LULC simulation tools such as Cellular Automata (CA) and Markov, are integrated with InVEST to provide predicted LULC spatial data to compute future carbon sequestration and benefits (Liang et al., 2017; Zhao et al., 2019).

The Cellular automata (CA) or hybrid model integrating the capabilities of both CA and Markov model (CA-Markov) is the most widely used technique to monitor and predict LULC changes (Liping et al., 2018; Li et al., 2019; Zhao et al., 2019). The Markov chain model is capable to make long term predictions summarizing change in any area by a series of transition probabilities from one state to the other over a set time frame. The CA model considers time and space as discrete units to simulate spatial variation in land cover (Liping et al., 2018). This CA-Markov model is preferred over other modeling techniques for its high efficiency, dynamic simulation capabilities, simple calibration and its ability to simulate multiple land covers and complex patterns (Sil et al., 2017).

A number of studies have been conducted on quantification and mapping of ecosystem carbon storage and sequestration. Liang et al. (2017) reported 0.8% increase in oasis carbon storage during 2000 to 2009 but decrease in it by 0.93% during the simulated period (2009 to 2018) due to LULC changes in China. Sil et al. (2017) reported increase in the magnitude and economic value of carbon stored in the observed (1990 - 2006) and simulated (2006 - 2020) land cover in the mountain river basin of Portugal. Zhao et al. (2018) reported 13.8% increase in carbon storage due to land cover changes in Qinghai-Tibet Plateau during 2001 to 2010. Simulation of LULC changes in the mountain-oasis desert ecosystem in China (during 2015 to 2035) showed an overall increase in carbon sequestration service, but some decrease in it at certain locations (Fu et al., 2018). Rimal et al. (2019) observed increase in forest area but decrease in ecosystem carbon storage due to loss of shrub land during 1996 to 2016 in Koshi River Basin in Nepal. Zhao et al. (2019) predicted increase in ecosystem carbon storage by 10.27 Tg under LULC changes from the ecological engineering program during 2015 to 2029 in Northwest China. Li et al. (2020)

predicted 1.36% increase in the forest area and carbon storage of Beijing China during 2015 to 2030 under LULC changes. Negassa et al. (2020) observed 23.68% per annum increase in the agriculture area and 4.18% per annum decrease in the forest area during 1991 to 2019 causing loss of ecosystem services in the Komto Protected Area, Ethiopia.

The carbon storage potential of the terrestrial ecosystems is greatly affected by climatic changes (Sun et al., 2020). Anthropogenic activities are largely responsible for the gradual rise in the mean global temperature. In response to the rising GHG concentrations the IPCC scenarios suggest warming between 2.6 – 4.8ºC by year 2100. The impacts of this warming are expected to occur on land surfaces making terrestrial ecosystems more prone to the impacts of climate change (IPCC, 2014; Zhai et al., 2018; Li et al., 2020). Studies have reported significant reduction in the ecological benefits in response to climatic changes (Gray & Brady, 2016; Deb et al., 2018; Wu et al., 2020). Warming has caused decline in forest cover and biodiversity, increased tree mortality, altered species composition and rate of nutrient cycling in tropical and subtropical forests (Verbesselt et al., 2016; Deb et al., 2018; Ding et al., 2019; Li et al., 2020).

Leaf litter fall and decomposition are fundamental ecosystem processes playing crucial roles in soil organic carbon (SOC) accumulation and replenishing nutrients necessary for plant growth (Santonja et al., 2015; Krishna & Mohan, 2017). The rate of litter decomposition is affected by number of factors including inherent litter quality, microbial enzymes, species composition, topography, seasonal variations, humidity, rainfall and climatic factors (Innangi et al., 2015; Gregorich et al., 2017; Krishna & Mohan, 2017; Horodecki & Jagodzi´nski, 2019; Stuble et al., 2019; Giweta, 2020). Any disturbances in these factors or acceleration of rate of decomposition under warming can result in positive feedback to climate change (Strickland et al., 2015; Romero-Olivares et al., 2017; Gregorich et al., 2017). Climatic changes not only alters microbial enzyme activity affecting the rate of litter decomposition, but also affects the biochemical composition of plant litter produced in an ecosystem (Petraglia et al., 2018; Stuble et al., 2019).

To gain insights into climatic controls of litter decomposition and nutrient cycling it is important to investigate decomposition dynamics across regions of varying climate.

Rate of litter decomposition and CO_2 efflux differed considerably among tropical lowland and montane forests of Malaysia during a 480 days litter bag incubation experiment. Due to the difference in the site climate, high rate of decomposition (k = 0.004 day^{-1}) and mass loss (> 80%) was observed in lowland tropical forest compared to the montane forest. Low decomposition rate (38%) and soil CO_2 efflux (two to three folds) was recorded in the montane forests indicating their role as temporary sink of carbon (Jeyanny et al., 2015). Innangi et al. (2015) investigated the decomposition of beech leaf litter in two Mediterranean forests in southern (warm) and northern (cold) Italy. Leaf litter decomposition was carried both in the field and in laboratory microcosms under temperature (8°C, 15°C and 22°C) manipulations. After 680 days of incubation, southern site was recorded with accelerated decomposition (k = 0.00069 days^{-1}) than northern site (k = 0.00051 days^{-1}) but the trend was reversed in the microcosms due to microbial adaptations to climatic changes. Portillo-Estrada et al. (2016) conducted litter transplantation experiments across six sites in Europe (two grasslands and four forests) with climatic differences (511 – 878 mm precipitation and 5.6 – 11.4^{o}C temperature). The warmer and wetter sites were recorded with high rate of decomposition than drier and colder sites. Climatic variables (temperature and precipitation) were found important predictors of residual weight of litter during decomposition.

Climatic warming is reported to significantly reduce litter half life (residence time) due to accelerated pace of decomposition. Bothwell et al. (2014) reported a positive linear function of temperature with litter decomposition in wet tropical forest of Hawaii Island. Warming (+1°C) accelerated the pace of litter decomposition and reduced litter residence time by 31 days. After six months of decomposition, litter nitrogen (N) decreased with increasing temperature suggesting that N will no more be a limiting factor for ecosystem productivity under warming. Gregorich et al. (2017) estimated reduction of 1 to 4 months and 1 to 2 years in the half life of labile and recalcitrant litter fractions respectively under warming in Canada.

Changes in soil temperature and moisture derive shifts in the rate of soil respiration. In terrestrial ecosystems, soil respiration adds 20% of the CO_2 emissions from soil to the atmosphere (Krishna & Mohan, 2017). Lin et al. (2011) reported increase in soil respiration by 9.2% under long term (3 years) warming (+1.2^{o}C/1.7^{o}C day/night)

The Art of writing only for samples use

during *in situ* decomposition of leaf litter in Tibetan plateau. The study also reported 19 – 34% variance in soil respiration due to temperature. The rate of soil CO_2 efflux and litter mass loss doubled with +3°C increase in the temperature at three sites in Mpumalanga province, South Africa (Salah & Scoles, 2011). Increase in carbon mineralization from 80 mgC in control (9°C and 45% soil moisture) to 100 mgC and 120 mgC under warming of +3°C and +6°C respectively with 75% of soil moisture was observed in a microcosm litter decomposition experiment (Butenschoen & Scheu, 2014). Warming (+2°C) increased the rate of heterotrophic respiration by 62% during an *in situ* heating experiment in temperate Sitka spruce plantation in Ireland. The rate of soil respiration remained unaffected under water additions (Zou et al., 2018). Stuble et al. (2019) also reported 40% and 12% increase in the rate of soil CO_2 efflux during long term *in situ* (14 years) and short term (120 days) microcosm warming (+3°C) experiments respectively.

Changes in precipitation regime also significantly influences litter decomposition and rate of soil CO_2 efflux. Yoon et al. (2014) reported increase in soil CO_2 efflux from 221 mgC/m^{2}h to 324 mgC/m^{2}h from poorly drained and well drained soils respectively in Japanese alder forest, Korea. Deng et al. (2017) conducted a rain simulation experiment and reported 83% increase in soil CO_2 efflux after rain in a subtropical forest in China. Yu et al. (2018) documented significant effect (p < 0.01) of precipitation on litter mass loss during a precipitation manipulation experiment carried out at Xiaoliang tropical research station in China. Increase in litter mass loss (~ 0.1%/day) was observed with 60% increase in precipitation during dry season. Decrease in litter decomposition rate (5%) due to warming induced reduction in litter moisture was reported by Chuckran et al. (2020).

The rate of decomposition of labile and recalcitrant carbon fractions determines the soil organic carbon accumulation. Romero-Olivares et al. (2017) reported that mass loss of recalcitrant carbon fractions was higher (0.8 g) compared to labile fractions due to sensitivity of lignin degrading enzymes to warming (+1.6^{o}C) in boreal forest, Alaska. However, Stuble et al. (2019) reported accelerated decomposition of the labile carbon fractions compared to recalcitrant fractions during long term (14 years) field warming (+3°C) experiment in Oklahoma. The rate of decomposition of labile fractions increased from 13% to 23% under warming suggesting a faster nutrient

The Art of writing only for samples use

turnover in future. Elevated temperature increases the activity of microbial enzymes promoting leaching of labile and recalcitrant fractions (Amani et al., 2019).

The rising level of atmospheric CO_2 concentration influences litter chemistry and rate of nutrient turnover in terrestrial ecosystems. Cha et al. (2017) exposed *Fraxinus rhynchophylla* and *Quercus acutissima* seedlings to elevated CO_2 levels and observed alteration in leaf nutrient allocation compared to the ambient level of CO_2. Both species produced leaf litter with increased lignin concentration, lignin/N and C/N ratio but decrease in leaf nitrogen level. Elevated CO_2 suppressed the rate of decomposition due to accumulation of recalcitrant fractions and low leaf N and microbial biomass. A meta-analysis of 41 studies conducted across the globe reported decrease in litter decomposition under elevated levels of CO_2. High levels of CO_2 change the physiology and biochemistry of leaf by increasing the concentration of recalcitrant carbon fractions which tend to decompose at slower rate (Amani et al., 2019). Rai et al. (2020) exposed seedlings of *Tectona grandis* and *Butea monosperma* to elevated CO_2 and observed decrease in litter decomposition due to higher foliar concentration of secondary carbon compounds.

The short term and long term temperature manipulations help in investigating the response of tree species to the impacts of predicted climatic warming. These studies are conducted either in the field under open to chambers (OTCs) or in plant growth chambers maintaining a set of experimental conditions (Angulo et al., 2019; Fauset et al., 2019). Such investigations are mostly conducted on tree seedlings as those are considered more sensitive to environmental changes than adult plants (Angulo et al., 2019; Wu et al., 2019; Li et al., 2020).

Several studies investigated the positive and negative impacts of elevated temperature on physiology, biochemistry and growth of forest ecosystems. Li et al. (2016) investigated the impact of warming (+1°C) on photosynthetic rate of six evergreen subtropical tree species i.e. *Schima superba*, *Machilus breviflora*, *Pinus massoniana*, *Synzigium rehderianum*, *Castanopsis hystrix* and *Ardisia lindleyana*. The long term warming (2 years) increased the rate of photosynthesis by 7%, 19%, 20% and 29% for *S. superba*, *M. breviflora*, *P. massoniana* and *A. lindleyana* respectively but it declined in other two species. The study found that warming could significantly alter ecosystem structure in the long run. Another study reported decrease in stomatal

The Art of writing only for samples use

density, stomatal conductance, photosynthetic rate and carbon accumulation in *S. superba* under +2°C warming during short term (1 year) exposure. The effect of warming remained insignificant in case of *S. rehderianum* indicating increased susceptibility of *S. superba* to climatic changes (Wu et al., 2018). High photosynthetic rate of *S. superba*, *M. breviflora*, *S. rehderianum* and *Itea chinensis* under +2°C warming was also reported by Wu et al. (2020).

Warming induces species specific differences in the growth rate and biomass accumulation in seedlings. Noh et al. (2016) documented interspecific differences in seedling biomass accumulation and soil CO_2 efflux of deciduous (*Quercus variabilis*) and evergreen species (*Pinus densiflora*). No significant effect of temperature was observed on biomass accumulation of both species. However, shoot and root biomass of *Q. variabilis* was 0.9 kg/m^2 and 0.6 kg/m^2 higher under warming than control. Biomass accumulation in *P. densiflora* decreased in response to warming. The soil CO_2 efflux was 22% and 29% higher under warming in *P. densiflora* and *Q. variabilis* plots highlighting decrease in future soil carbon stock.

Seedlings of six subtropical tree species were exposed to +3°C warming for 3 years. Significant effect of warming and species type was observed on seedling height (p < 0.001) and biomass accumulation (p < 0.05). Warming significantly increased biomass accumulation in *S. superba*, and *P. densiflora* but decreased the specific leaf area compared to *C. hystrix*, *M. breviflora*, *S. rehderanum* and *A. lindliyana*. The concentration of soluble sugars and starch was also reduced under warming (Li et al., 2017). In a meta-analysis study based on biomass dataset of 1081 forests, low stem mass ratio was observed in response to warming. However, high precipitation rates increased leaf and root mass fractions (Fang et al., 2018).

Warming (+1.5^{o}C) promoted stem growth and increased height and girth of *S. superba*, *S. rehderanum* and *Itea chinensis* during a long term (4 years) translocation experiment conducted in tropical biosphere reserve in China (Wu et al., 2019; Li et al., 2020). Wu et al. (2020) also documented increase in biomass accumulation of *S. superba*, *Itea chinensis* and *Syzigium rehderianum* but it decreased in *M. breviflora* when exposed to +6°C warming for six years. Interspecific differences in the biomass allocation were also observed. The biomass allocation to roots was 34% higher in *M.*

breviflora, while other species allocated more biomass to the stem at expense of roots suggesting possible alterations in the species composition in future.

Warming and changes in precipitation affect root development. Han et al. (2018) investigated the effect of warming (+3ºC) and changes in precipitation (± 30%) on root development of *P. densiflora*. Warming reduced fine root mortality by 13% however, 29% and 69% increase in the root production and root biomass was observed in seedlings exposed to 30% reduction in precipitation. Xiong et al. (2018) also documented positive effect of warming (+5ºC) on fine root production and seedling survival of *Cunninghamia lanceolata* dominated subtropical plantation in China.

Climatic changes not only alter plant biomass accumulation but it also affect the leaf biochemistry and nutrient dynamics of an ecosystem. Low moisture availability and warming reduced leaf area and foliar C:N ratio in *Acer rubrum, Ulmus americana, Prunus serotina* and *Betula lenta* indicating susceptibility of these species to warm (4ºC) dry conditions (−50% precipitation) (Rodgers et al., 2018). Zhang et al. (2019) reported increase in foliar nitrogen concentration (by 57%) in *Cunnighamia lanceolata* when exposed to short term warming (+5ºC) and decrease in precipitation (–50%). Wu et al. (2019) reported decrease in leaf N under +1.5ºC warming while interspecific differences in the leaf C concentration were also observed. The leaf C concentration of *S. superba* was reduced by 5% but it increased in *I. chinensis* in response to warming. Wu et al. (2020) documented increase in N productivity by 35% in *S. rehderanum* but 40% and 60% decrease in N and P productivity of *I. chinensis* and *M. breviflora* respectively when exposed to +6ºC warming for six years.

Climate change also significantly alters seed germination and seedling survival. Rodgers et al. (2018) exposed deciduous temperate tree species to range of warming (1.3ºC to 4ºC) and precipitation (±50%) conditions. Seedling survival rate of *Populus grandidentata* was high (83%) under low warming (1.3ºC) and high moisture availability (+50%) but it decreased to 40% with increase in temperature. Seedling mortality was low (< 13%) in *Quercus rubra, Ulmus americana* and *Betula lenta*. Taccoen et al. (2021) also documented increase in tree mortality with changes in temperature and precipitation.

Kim and Han (2018) investigated the effect of +3ºC warming and elevated CO_2 (750 ppm) on seed germination of needle and broadleaved species. Warming significantly affected seed germination of *P. densiflora* ($p < 0.05$), *Betula ermanii* ($p < 0.05$), *Maakia amurensis* ($p < 0.05$) and *Pinus thunbergii* ($p < 0.001$) however elevated CO_2 affected seed germination of *Picea jezoensis* ($p < 0.05$) only. The combined effect of elevated temperature and CO_2 affected germination percentage of *Zelkova serrata* and *Malus baccata* ($p < 0.05$). High growth temperatures (+5ºC and +10ºC) inhibited seed germination of *Pinus bungeana* (Guo et al., 2020).

Elevated levels of CO_2 induce fertilization effect and alter growth pattern and C-N-P stoichiometry of terrestrial plants. Higher concentration of CO_2 increase root length and promote development of root nodules (Gray & Brady, 2016). Elevated CO_2 concentration increases leaf area by maximizing water use efficiency. This results in increase in the photosynthetic rate and production of secondary carbon compounds (Gray & Brady, 2016; Amani et al., 2019; Cernusak et al., 2019; Rai et al., 2020). A meta-analysis of 4481 observations also reported 2.2% and 13% increase in plant C and C:N respectively but decrease in N (9.3%), P (3.2%) and N:P (7.3%) when exposed to elevated CO_2 concentration (Du et al., 2019).

Pakistan contributes only 0.7% to the total global CO_2 emissions but its geographic location, socioeconomic profile and lack of adaptive capacity make it vulnerable to the impacts of climate change (Chaudhry, 2017). The Intergovernmental Panel on Climate Change (IPCC) has suggested warming of +2.3ºC and +4.5ºC under RCP 2.6 and RCP 8.5 (Representative Concentration Pathways) scenarios respectively and some increase in precipitation (< 10%) for Pakistan by the end of this century (Cruz et al., 2007; CDKN, 2014; Hijioka et al., 2014; Chaudhry, 2017; IPCC, 2020). These RCP pathways represent the lowest (2.6) and highest (8.5) GHG emission scenarios and the number(s) corresponds to the GHG radiative forcing by year 2100 (Nazarenko et al., 2015). During last six decades, rise of 0.6ºC to 1ºC in the mean annual temperature and 18 – 32% increase in the monsoon rainfall has been observed in Pakistan. It is expected that the projected rise in temperature and precipitation would severely affect country's forest ecosystems (Hijioka et al., 2014; Chaudhry, 2017). But there exist gap in research to investigate the impacts of predicted warming and precipitation changes on regulatory ecosystem services in Pakistan.

Siddiqui et al. (1999) simulated the impact of changes in CO_2 concentration (425, 500 and 575 ppm), precipitation (0 and ±3%) and temperature (0.9ºC, 1.8ºC and 2.7ºC) on forest cover in Pakistan during 2020, 2050 and 2080. The study reported decline in the cover of semi-arid scrub forest, alpine tundra and arid shrub lands but increase in temperate coniferous forests. The LULC simulations reported reduction in the country's forest carbon stock by 4% in 2020 compared to the estimates of 2009 under business as usual scenario (Chen et al., 2017). Mannan et al. (2019) simulated the impact of LULC changes on subtropical chirpine and moist temperate forest in Pakistan and estimated significant decrease in forest area and loss of 31.33 GgC/ha/yr during simulated (2028) period. Waseem and Khayyam (2019) reported 22% to 51% decline in vegetative cover of Islamabad city (federal capital of Pakistan) over a time span of 25 years (1992-2017) with increase in land surface temperature from 13–27ºC/year to 23–43ºC/year. Considering this research gap, current study was designed to assess current carbon stock and provide experiment based evidence of impacts of predicted climatic warming and precipitation changes on carbon storage and sequestration potential of the subtropical scrub forest in Pakistan.

Chapter 3

ASSESSMENT OF TREE BIOMASS CARBON STOCK OF SUBTROPICAL SCRUB FOREST, SOAN VALLEY PAKISTAN

3.1. INTRODUCTION

Forests mitigate global climate crisis by storing four times more carbon in the vegetation and soil than it exists in the atmosphere (Issa et al., 2020). The REDD+ (Reducing Emissions from Deforestation and Forest Degradation, conservation, enhancement and sustainable management) provides financial incentives to the developing countries for reducing their carbon emissions and enhancing carbon sinks. It is mandatory for the signatory countries to periodically report their forest carbon stock to qualify for REDD+ incentives (Yuan et al., 2016). The quantification and reporting of biomass carbon stock helps in assessing ecosystem productivity and efforts of forestry sector in mitigating the impacts of climate change (Mukuralinda et al., 2021). The assessment of carbon stock is influenced by the choice of method selected due to differences in the tree biophysical factors incorporated into the biomass allometric model (Picard et al., 2015; Zhao et al., 2019). These models are either species or site/region specific (generic models) and may incorporate one, two or more biophysical factors in the model causing variation in the estimates (Chave et al., 2014; Vargas-Larreta et al., 2017; Kebede & Soromessa, 2018; Zhao et al., 2019; Mukuralinda et al., 2021). In Pakistan the lack of development for local biomass allometric models often lead to the use of simple generic volume models which may generate erroneous carbon estimates. The volume models are now less recommended due to the use of fixed tree form factors and also because of their limited utility in the closed canopy forests (Wang et al., 2019; Socha et al., 2020). This research was designed to assess the biomass carbon stock of the Hayat-ul-Mir (HM) subtropical scrub forest, and is first of its kind in Pakistan to check the robustness of existing generic models against local allometric models. The local biomass allometric models were used as a bench mark and the estimates were compared with pantropical generic biomass allometric model of Chave et al. (2014) and i-Tree Eco tool. It was

hypothesized that increase in the number of variables in the biomass allometric model will generate more reliable estimates.

3.2. MATERIALS AND METHODS

3.2.1. Field data collection

Field data collection was done during November 2017 to December 2018 for the non-destructive estimation of tree biomass carbon stock of the Hayat-ul-Mir (HM) forest. For this purpose, 47 survey plots of 0.04 ha (20 m × 20 m) were taken in the forest at random and sufficient distance from each other (Figure 3.1). For the estimation of tree above ground biomass (AGB), tree dendrometric variables such as DBH (Diameter at Breast Height) and Ht (tree height) was measured following UNFCCC protocols. For multi-stems trees which forked below the height of 1.3 m, individual diameter of each stem was recorded, and square root of the sum of DBH squares was taken to produce single DBH value following Equation 3.1. Trees with < 2.5 cm were not considered. Tree basal area (BA) and volume was computed following Equation 3.2 and 3.3 (Nizami, 2012).

$$\mathbf{DBH = sqrt[DBH_1^2 + DBH_2^2 + \ldots DBH_n^2]} \qquad \text{...Eq. (3.1)}$$

$$\mathbf{Basal\ Area = \pi/4 \times DBH^2} \qquad \text{...Eq. (3.2)}$$

$$\mathbf{Tree\ volume\ (m^3) = (\pi/4) \times DBH^2 \times F \times Ht} \qquad \text{...Eq. (3.3)}$$

Where

DBH is Diameter at Breast Height, Ht is tree height and F is the tree form factor. Depending on the highest and lowest DBH and Ht recorded of both species in the HM forest, eight DBH classes (< 1 cm to 76 cm) and six height classes (< 2 m to 10 m) were made. Visual estimations were made to assess health of the trees based on percentage dieback of branches in the crown and seven dieback classes were made ranging from excellent crown (<1% dieback) to dead crown with 100% dieback (Nowak et al., 2008) (Table 3.1). Species importance value index (IVI) was calculated following Philips (1959) using Equation 3.4.

The Art of writing only for samples use

$$\mathbf{IVI = relative\ frequency + relative\ density + relative\ dominance} \qquad \text{...Eq. (3.4)}$$

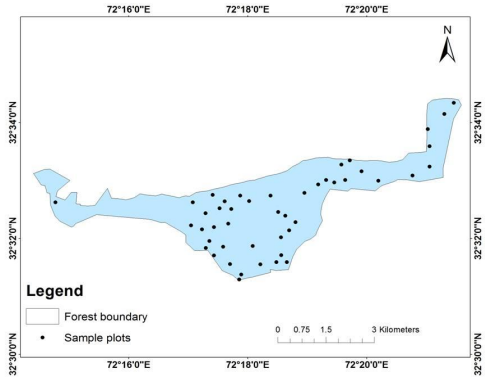

Figure 3.1: Spatial distribution of survey plots taken in the Hayat-ul-Mir forest

Table 3.1: Classification of structural attributes of the HM forest.

DBH (cm)		Height (m)		Crown dieback (%)	
Class	**Range**	**Class**	**Range**	**Category**	**Dieback (%)**
I	< 1 – 7.6	I	< 2	Excellent	< 1
II	7.6 – 15.2	II	2 – 4	Good	1 – 10
III	15.2 – 22.9	III	4 – 6	Fair	11 – 25
IV	22.9 – 30.5	IV	6 – 8	Poor	26 – 50
V	30.5 – 38.1	V	8 – 10	Critical	51 – 75
VI	38.1 – 45.7	VI	> 10	Dying	76 – 99
VII	45.7 – 53.3			Dead	100
VIII	68.6 – 76.2				

The Art of writing only for samples use

3.2.2. Estimation of tree biomass

Locally developed species specific volume allometric models were used to estimate the aboveground biomass of *O. ferruginea* and *A. modesta* in the HM Forest. These equations were used as a reference to evaluate the robustness and applicability of two existing non-destructive generic biomass allometric models. This study is first of its kind to refine and calibrate existing generic allometric models against local models for accurate carbon accounting of the subtropical forest under REDD+ in Pakistan.

3.2.2.1. AGB estimation through local volume equations

Local harvest based volume allometric equations for *A. modesta* and *O. ferruginea* were developed by Pakistan Forest Institute (1993) after destructively harvesting trees across diverse DBH (6 – 64 cm) and height (2.86 – 11.15 m) ranges in the non-irrigated area of North West Frontier Province (now Khyber Pakhtunkhwa) of Pakistan (Annexure I). Total volume of *A. modesta* and *O. ferruginea* was estimated following Equation 3.5 and Equation 3.6 respectively;

$$\mathbf{\mathit{ln}TV = -9.35092 + 0.36032\ \mathit{ln}H + 2.22653\mathit{ln}D} \qquad \text{...Eq. (3.5)}$$

$$\mathbf{\mathit{ln}TV = -9.3826 + 0.56528\mathit{ln}H + 2.09297\mathit{ln}D} \qquad \text{...Eq. (3.6)}$$

Where *ln* is the natural logarithm, TV is the total tree volume (m^3), H is the height (m) and D is the Diameter at Breast Height (cm). These equations helped in computing individual tree volume of bi-climax community of the HM forest. The tree volume was then multiplied with species specific wood density (WD) to compute aboveground biomass (AGB) following Nizami (2012). The species specific wood densities (WD) of the bi-climax community were adopted from World Agroforestry Database (Pearson & Brown 1932). The database provided 0.835 gcm^{-3} and 1.0135 gcm^{-3} species specific WD for *A. modesta* and *O. ferruginea* respectively.

3.2.2.2. AGB estimation using generic pantropical allometric model

The generic pantropical biomass allometric equation (Model 4 from Chave et al. 2014) was used to estimate AGB of *A. modesta* and *O. ferruginea* against the product

The Art of writing only for samples use

of height (m), DBH (cm) and species specific wood density (gcm^{-3}). This model (based on harvest data from 58 sites across tropics with variable vegetation and climatic conditions) is a revised and improved version of Chave et al. (2005) and was selected as it performs well across forest types in pantropical bioclimatic conditions (Equation 3.7). The model is reported with slightly high variance and mean percent bias when compared with local models, but no detectable effect of environmental factors or region on AGB considering Ht, DBH and WD as covariates. The previous version (Chave et al., 2005) of this model has been evaluated by Kebede and Soromessa (2018) for *O. europea* L. sub sp. *cuspidata* (synonym *O. ferruginea*) in Ethiopia where allometric equations were developed through semi-destructive harvest and were compared with species specific and generic allometric models. This model has also been previously documented for *O. europea* by Tesfaye et al. (2016) and Muhati et al. (2018).

$$\mathbf{AGB_{est}\ (kg) = 0.0673 \times (\rho D^2 H)^{0.976}} \qquad \text{...Eq. (3.7)}$$

Where ρ is species specific wood density, D is DBH and H is tree height. From the aboveground biomass estimates made through harvest based local equations and generic pantropical allometric model of Chave et al. (2014) (Equations 3.5 to 3.7), belowground biomass (BGB) was calculated as 26% of the AGB (Nowak et al., 2008). Total tree biomass (TB) was obtained after taking sum of AGB and BGB across individuals of both species. TB was converted into total tree biomass carbon (TBC) by multiplying with IPCC default factor of 0.50 as carbon accounts for 50% of the total biomass.

3.2.2.3. Calculation of tree carbon storage through i-Tree Eco tool

i-Tree Eco tool (version 6.0) was used to estimate total biomass and carbon stock of *A. modesta* and *O. ferruginea* in the HM forest. For this purpose, hourly annual metrological data of the site and field measurements of DBH, crown height, total tree height, crown dieback and crown light exposure (CLE) data was input into the tool to quantify total tree dry weight and carbon storage using species specific allometric equation. Crown light exposure was estimated considering number of sides of the crown exposed to sunlight following Bechtold (2003). The total tree (above and belowground) carbon in *A. modesta* and *O. ferruginea* was calculated using equation

form 1 in the tool database (Equation 3.8). This tool was selected for being a novel approach which has not yet been used for tree species in Pakistan and also it additionally quantifies other ecosystem services along with biomass estimates.

Carbon Storage = exp((A + B * log(Variable) + (Mean Squared Error /2)/2

...Eq. (3.8)

Where A and B are coefficients and Variable is DBH (in case of *A. modesta*) or DBH & Height (in case of *O. ferruginea*). The total tree dry weight biomass (including 26% of the belowground biomass) was converted to carbon stock by multiplying with a factor of 0.5.

The plot based (0.04 ha) biomass estimates were up-scaled to hectare level using an appropriate area based conversion factor and both existing methods were evaluated against locally developed equations to choose the best fit model for carbon stock assessment of the subtropical forest in Pakistan.

3.2.3. Data Analysis

For data analysis, SPSS v. 21 (Statistical Package for Social Sciences) was used. Independent sample *t*-test was performed to evaluate statistical relationship between biophysical factors (dendrometric factors) of the surveyed population of both species. Mean and standard errors of biomass and carbon estimates were computed to compare for the variation in estimates made using local and generic models. Multiple comparisons were made using Repeated Measures ANOVA (Analysis of Variance) and Bonferroni statistics was used to find the significant differences in carbon storage estimates made by each method used in this study. Multiple linear and logistic regression analyses were also run to choose the best fit model based on their relative performance considering TB as dependent and biophysical factors (DBH, Ht, & WD) as independent variables. The analysis was done to find the significance of biophysical factors in predicting tree biomass. Goodness of fit statistics was considered for a model which had high value of R^2-adj., lowest AIC (Aikaike Information criteria), BIC (Bayesian Information Criteria), RMSE (Root Mean Square Error) and $p \leq 0.05$.

The Art of writing only for samples use

3.3. RESULTS

3.3.1. Structural summary of the forest

In the HM forest, a total population of 399 trees (135 trees of *A. modesta* and 264 trees of *O. ferruginea*) was recorded in 47 survey plots (0.04 ha). Forest dendrometric characteristics have been presented in Table 3.2. *O. ferruginea* had higher tree density (150 trees/ha) and the importance value (IVI) of 176 than *A. modesta* (82 trees/ha) with IVI of 123. There was a significant difference in tree height (t = 3.76, df = 397, p < 0.001), DBH (t = 3.11, df = 397, p < 0.01) and basal area (t = 3.14, df = 397, p < 0.05) of both species but not in case of tree volume (t = -0.251, df = 83, p = 0.802). Highest mean DBH (20.69 ± 0.8 cm) and height (5.94 ± 0.1 m) was recorded for *A. modesta* and highest basal area (4.46 ± 0.6 m^2/ha) and tree volume (17.10 ± 2.4 m^3/ha) was recorded for *O. ferruginea* in the survey plots.

The Art of writing only for samples use

Table 3.2: Dendrometric characteristics of the Hayat-ul-Mir Forest

Species	Trees /ha	IVI	Height (m)			DBH (cm)			Basal area (m^2/ha)	Tree volume (m^3/ha)
			Min.	Max.	*M ± SE*	Min.	Max.	*M ± SE*	*M ± SE*	*M ± SE*
A. modesta	82	123	1.83	10.67	5.94 ± 0.1***	4.10	71.00	20.69 ± 0.8**	3.44 ± 0.4	16.22 ± 2.6
O. ferruginea	150	176	1.83	10.67	5.15 ± 0.1	3.80	43.20	17.78 ± 0.4	4.46 ± 0.6*	17.10 ± 2.4

***p < 0.001, **p < 0.01, *p < 0.05

The Art of writing only for samples use

Figure 3.2 presents the diameter and height distribution of individuals of both species in the HM forest. Only a small proportion of the population of both species was recorded within DBH Class I (3.6% of *A. modesta* and 2.7% of *O. ferruginea*) and class VI to VIII (2.4% of *A. modesta* and 0.5% of *O. ferruginea* combined). However, collectively 57% and 74% population of *A. modesta* and *O. ferruginea* respectively, was recorded in the second and third DBH classes (ranging 7.6 – 22.9 cm). A similar kind of trend in the relative distribution of population of both species was observed in the height classes. A very small proportion of the population of both species (5.7% of *A. modesta* and 3.1% of *O. ferruginea* combined) was found in the lowest and highest height class. Collectively 82% and 91% population of *A. modesta* and *O. ferruginea* respectively was recorded with height 2 – 8 m.

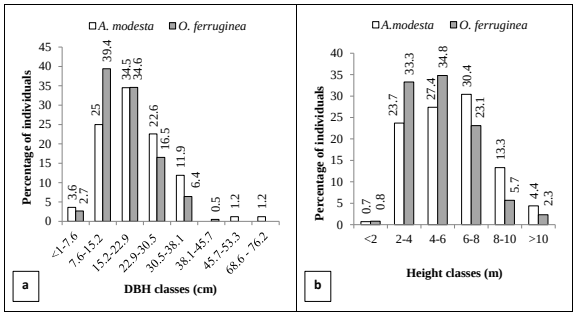

Fig. 3.2: Tree distribution in (a) DBH and (b) height classes in sampled plots of HM forest

Figure 3.3 illustrates the overall health of the forest classified on the basis of crown dieback. The majority of the trees (*A. modesta* 51.1% and *O. ferruginea* 49.2%) were in good health condition with 1% - 10% crown dieback. The rest of the trees were either in an excellent (*A. modesta* 40% and *O. ferruginea* 43.2%) or fair (*A. modesta* 8.1% and *O. ferruginea* 6.8%) state of health with <1% and 11-25% crown dieback, respectively. A very small proportion of individuals of both species were found in poor (26% - 50%) and dying (76% - 99%) crown health classes.

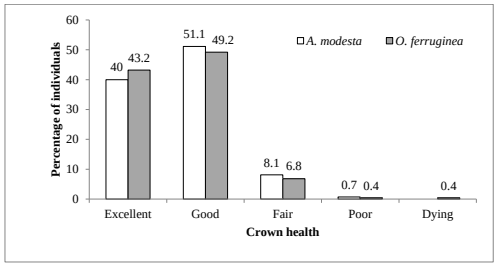

Figure 3.3: Health of the forest based on percentage crown dieback of sampled trees

3.3.2. Tree biomass and carbon storage

The generic methods of biomass estimation used in this study produced comparable estimates for both species when evaluated against locally developed equations. Table 3.3 shows plot scale TB and TBC of sampled population. The generic allometric equation of Chave et al. (2014) produced slightly higher (70.88 Mg and 35.44 Mg) while i-Tree Eco tool produced lower (58.77 Mg and 29.38 Mg) TB and TBC estimates compared to the species specific local equations for bi-climax community (67.12 Mg and 33.56 Mg). Individual tree based estimates are available in Annexure II.

Table 3.3: Total tree biomass and carbon storage in 47 survey plots (each plot of 0.04 ha)

Species	Tree biomass (Mg)			Tree biomass carbon (Mg)		
	Local Eq.	Chave et al. (2014)	i-Tree Eco	Local Eq.	Chave et al. (2014)	i-Tree Eco
A. modesta	28.66	28.96	16.97	14.33	14.48	8.48
O. ferruginea	38.45	41.92	41.80	19.22	20.96	20.90
Total	67.12	70.88	58.77	33.56	35.44	29.38

Figure 3.4 (a & b) illustrates the mean of TB and TBC of both species of scrub forest estimated using the selected methods. It can be seen from figure below that i-Tree Eco produced lower TB and TBC estimates (10.34 Mg/ha and 5.17 Mg/ha) than generic pantropical allometric equation (17.36 Mg/ha and 8.68 Mg/ha) and local (17.06 Mg/ha and 8.53 Mg/ha) allometric equations when evaluated for *A. modesta*. However, in case of *O. ferruginea* both existing methods produced comparable but slightly higher estimates than local equation.

Repeated measures ANOVA with Greenhouse-Geisser correction showed that mean TB and TBC significantly differed between the methods for *A. modesta* ($F(1.536, 205.78) = 31.22$, $p = 0.000$) but not for *O. ferruginea* ($F(1.429, 375.78) = 2.162$, $p = 0.132$). For *A. modesta*, Post hoc test using Bonferroni correction revealed that the TB and TBC estimates of generic pantropical allometric equation of Chave et al. (2014) were not significantly different from the estimates of local equation ($p = 1.000$) but differed significantly in case of i-Tree Eco ($p = 0.000$) as shown in Figure 3.4.

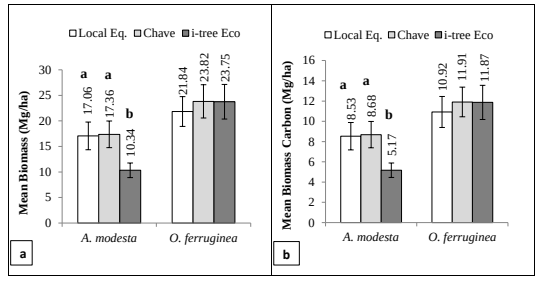

Figure 3.4: Mean of (a) total biomass (TB) and (b) total biomass carbon (TBC) calculated using three different methods (bars with similar letters are not significantly different at $p \geq 0.05$)

3.3.3. Model assessment

The results of multiple linear regression analysis (Table 3.4) showed that the covariate DBH was statistically significant ($p < 0.001$) in all models for both species but height was not statistically significant in the local equations and i-Tree Eco (for *O. ferruginea* only). In case of both species, all of the models were good fit at $p < 0.001$ but highest R^2-adj. (0.802), lowest AIC, BIC and RMSE were reported by generic pantropical allometric model of Chave et al. (2014) for *A. modesta*. However, for *O. ferruginea* the highest R^2-adj. (0.809) and lowest RMSE (0.093) were reported by local equation and lowest AIC and BIC by Chave et al. (2014).

Table 3.4: Goodness of fit statistics of regression models for the prediction of TB across both species in the HM forest

Models	Selection Criteria				Biophysical variables
	AIC	BIC	R^2 adj.	RMSE	
Acacia modesta					
Local Equation	1402	2455	0.792***	0.186	DBH***, H
Chave et al. (2014)	1379	2399	0.802***	0.138	DBH***, H*
i-Tree Eco tool	2060	2803	0.738***	0.193	DBH***
Olea ferruginea					
Local Equation	4179	8013	0.809***	0.093	DBH***, H
Chave et al. (2014)	4057	7809	0.802***	0.104	DBH***, H***
i-Tree Eco tool	4253	8174	0.752***	0.137	DBH***, H

*** $p < 0.001$, * $p < 0.05$, AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria, RMSE = Root Mean Square Error

3.4. DISCUSSION

Among the two species investigated in the HM forest, *O. ferruginea* was the most dominant with high tree density than *A. modesta*. The average tree density of *A. modesta* in the HM forest was much lower than that reported for this species in Kherimurat (197 trees/ha) and Sohawa forests (179 trees/ha) in Pakistan. Maximum DBH (71 cm) of *A. modesta* recorded in this study was higher than that reported for Kherimurat and Sohawa forests (max. 36 cm) causing this species to occupy more

basal area (3.44 m^2/ha) and volume (16.22 m^3/ha) in the HM forest compared to Kherimurat (1.81 m^2/ha and 8.19 m^3/ha, respectively) and Sohawa forests (1.66 m^2/ha and 8.08 m^3/ha, respectively) in Pakistan as reported by Nizami (2012).

Tree density (150 trees/ha), maximum DBH (43.20 cm), basal area (4.46 m^2/ha) and volume (17.10 m^3/ha) of *O. ferruginea* recorded in this study was higher than Kherimurat (94 trees/ha, 1.25 m^2/ha, 4.67 m^3/ha) and Sohawa (56 trees/ha, 0.99 m^2/ha, 3.32 m^3/ha) forests with maximum DBH of 30 cm (Nizami, 2012). A number of factors may contribute to the difference in the basal area and volume of both species at HM, Kherimurat and Sohawa sub-tropical scrub forests (Table 3.5). One such factor might be the difference in the elevation of these forests affecting relative distribution of species. The maximum elevation range of *A. modesta* is up to 1200 m and for *O. ferruginea* is up to 2000 m from sea level (Sheikh, 1993). As Kherimurat and Sohawa forests are located at a lower elevation (348 m from sea level) so have higher density of *A. modesta* than *O. ferruginea*. However, in HM forest (457-1067 m from sea level) high tree density of *A. modesta* was observed on lower elevations and of *O. ferruginea* on higher elevations. One more reason for high tree density of *A. modesta* in Kherimurat and Sohawa forests is related to the management practices. The HM forest is a reserved forest so limited rights on collection of wood are granted to the adjoining communities but Kherimurat and Sohawa are protected forests where no such rights have been granted.

A species also shows variable growth rate among different forest stands due to differences in soil nutrient status, topography and climate. A species competition with its neighbors is also an important factor which determines its density in a forest stand. High tree density of *A. modesta* in Kherimurat and Sohawa forests might have led to a competition with its neighbors for space and nutrients causing individuals to restrict their growth producing shorter height and DBH than individuals of same species in the HM forest. Also tree dendrometric characters like height and DBH have a strong relationship with tree age. Young trees with low DBH and shorter heights tend to occupy less basal area and so produce less biomass.

In the HM forest, a significant difference was found in the height and DBH of both species. Among other factors like tree density, seasonal changes in forest structure and regeneration status, a species growth rate and ecological strategies adopted by any

species play an important role in affecting structural characteristics of a forest (Shaheen et al., 2016; Kebede & Soromessa, 2018). For instance, deciduous trees (*A. modesta*) tend to grow at a faster rate than evergreen species (*O. ferruginea*) and have a large leaf surface area in order to compensate for the reduction in growth after shedding leaves. However, evergreens tend to show slow growth, lower rate of photosynthesis and have low leaf surface areas investing more of their energy in producing tough leaves to withstand harsh weather conditions (Tomlinson et al., 2013).

This study provides a comparison of methods that can be used to predict the biomass carbon stock of subtropical forests in Pakistan. In this study both existing generic models compared against the locally developed equations showed goodness of fit statistics at $p < 0.001$. The individual significance of biophysical variables (DBH & Ht) in predicting TB was also assessed through regression analysis. In case of both species, the generic allometric model of Chave et al. (2014) was found better predicting TB considering both DBH and Ht. There was an insignificant relationship of height with TB showing that i-Tree Eco was predicting TB using DBH only suggesting utility of this tool to predict TB if height data is not available for these two species. i-Tree Eco provides a range of dataset of species specific allometric equations for many other species across diverse climatic range. The locally developed allometric equation for *A. modesta* and *O. ferruginea* also showed similar relation with DBH ($p < 0.001$) and tree height ($p = 0.793$ and $p = 0.104$, respectively) suggesting the relative importance of inclusion of individual biophysical variables in the local model.

Goodness of fit statistics of the models used in this study was evaluated on the basis of multiple criteria. Any model which had high value of R^2 adj., lowest AIC, BIC and RMSE was considered best model in predicting TB of bi-climax community of the HM forest. In case of this study, when compared to the locally developed allometric equations, the lowest AIC and BIC was found for the generic pantropical allometric model of Chave et al. (2014) for both species. This model also reported high value of R^2 adj. when evaluated for *A. modesta* but only slightly less than local equation for *O. ferruginea*. This generic model has originally been developed by taking harvest dataset of multiple species across the tropical region (Chave et al., 2014) and its evaluation in this study confirms its robustness and reliability for the forest carbon

The Art of writing only for samples use

stock assessment in the subtropical region of Pakistan as well. Results of this study are consistent to the findings of Kebede and Soromessa (2018), reporting goodness of fit statistics of four species specific allometric equations for *O. europea* sub sp. *cuspidata* (synonym of *O. ferruginea*) at $p < 0.001$ and found a strong correlation of AGB with DBH and height but insignificant relation with wood density. Similarly these results are also consistent to the findings of Vieilledent et al. (2012) who reported generic models of Chave et al. (2005) as more reliable and producing less bias for TBC estimates of tropical forests when compared with other generic models.

Among the biomass and carbon estimates, the post hoc test showed no significant difference between the estimates made with local equation and generic allometric equation of Chave et al. (2014) when compared for *A. modesta*, but i-Tree Eco significantly underestimated the TB and TBC. Reasons for this underestimation might be because i-Tree Eco considered DBH only for *A. modesta* in its equation form 1 and also it computes the weight of wood only in TBC estimates for the deciduous tree species (Nowak et al., 2008). i-Tree Eco relying on DBH only did not perform well with low R^2 adj. and high RMSE and AIC compared to the local and pantropical models. Similar results have been reported by Ruiz-Peinado et al. (2012), Huy et al. (2016) and Djomo and Chimi (2017) stating that inclusion of two (DBH & Ht) or three covariates (DBH, Ht & WD) in allometric models better predict biomass than models with DBH only as covariate. From this analysis it can be inferred that in the absence of local allometric equations or restriction in doing destructive harvest to accurately measure the TBC, the pantropical model of Chave et al. (2014) can be used as an alternative to better predict the TBC relying on the field measurements of DBH, height and wood density in subtropical forest.

In case of *O. ferruginea*, the post hoc test showed no significant difference in the means of TBC estimated with local equation and other two existing models. The analysis suggests that both existing models accurately estimated TBC for subtropical scrub forest compared to the local model and can be considered as equal candidate models in predicting TBC if the local equations are not available. In such case it could be advantageous to select the pantropical equation of Chave et al. (2014) than i-Tree Eco considering their relative values of AIC, BIC and R^2 adj.

The Art of writing only for samples use

Most of the biomass estimates in Pakistan are made using generic volume equation of Philip (1994) which draws simple geometric relationship between the basal area (Eq. 2), height (H) and form factor (F) multiplied with species specific wood density (ρ) of tree ($AGB = \rho \times [BA \times F \times H]$). This model was developed by foresters and is now seldom used in carbon accounting as it assumes fixed form factor and also cannot predict biomass if height data is not available in close canopy forests (Chave et al., 2005). A comparison of biomass estimates of this study has been made with other studies conducted on sub-tropical forests in Pakistan (Table 3.5). The TB estimates of *A. modesta* made using local allometric equation in this study are comparable to the findings of Nizami (2010, 2012) made through Philip (1994) in Kherimurat and Sohawa scrub forests in Pakistan. The species specific allometric equation used by Shaheen et al. (2016) underestimated the TB of *A. modesta* (12.7 t/ha) in the mixed forest at two sites in the Muzaffarabad District, Pakistan compared to the findings of this study. In case of *O. ferruginea* the TB was overestimated (approx. four times) with volume equation (Philip, 1994) in Shaheen et al. (2016) than current study. The difference in the estimates might be due to the incorporation of differentset of biophysical variables in species specific, generic allometric and simple volume equations in both studies. Other reasons for the difference in the estimates might be related to the tree density, topographic and climatic differences as the subtropical forest in Muzaffarabad district is at a higher elevation, has low temperature and receives higher rainfall than the HM forest as summarized in Table 3.5. Located at the foothills of lesser Himalaya the subtropical forest in Muzaffarabad district is also under anthropogenic threats (not a protected forest) and the local population rely heavily on forest for its needs related to timber, food, fodder and fuelwood resulting in under reporting of actual tree biomass and carbon (Shaheen et al., 2016).

The Art of writing only for samples use

Table 3.5: Comparison of biomass estimates of HM forest and other subtropical forests in Pakistan

Reference (Forest Type)	Study site	Elevation (m)	Legal status	Climate		*Acacia modesta* TB estimation method (Mg/ha)				*Olea ferruginea* TB estimation method (Mg/ha)			
				Temp. (°C)	Av. Rainfall (mm/yr)	Trees/ ha	Volume eq.	Allometric eq.	i-Tree Eco	Trees/ ha	Volume eq.	Allometric eq.	i-Tree Eco
Current study (Subtropical scrub)	Hayat-ul-Mir	457-1067	Reserved forest	24 (Av.)	800	74	17	17.4	10.3	152	21.8	23.8	23.8
Nizami (2010, 2012) (Subtropical scrub)	Kherimurat	348	Protected forest	38 (Max) 15 (Min)	750-780	197	15			94	35.7		
	Sohawa		Protected forest			179	15			56	25.3		
Shaheen et al. (2016) (Subtropical)	Muzaffarabad District	800-1300	NA	20 (Av.)	1511	NA		12.7		620	68.9		

NA = Not available

i-TreeEco has widely been used for the estimation of carbon storage and sequestration in urban forests across the United States and European countries. To the best of our knowledge none of the study citing i-Tree Eco for reporting carbon storage of tree species from Pakistan was found in the literature. The tool calculates carbon storage and sequestration using allometric equations based on natural forest-grown North American tree species and socan fairly be used for both natural and urban forests (Nowak et al., 2013; Russo et al., 2014). Results of this study (for *A. modesta*) are consistent to the findings of Russo et al. (2014) who compared the allometric equation against i-Tree Eco and CUFR Tree Carbon Calculator (CTCC) and reported the highest carbon storage value with the allometric equation (179.14 ton), followed by CTCC (140.15 ton) and lowest by i-Tree Eco (134.89 ton) in Bolzano's urban forest, Italy. Results of present study for *O. ferruginea* are contrary to the Aguaron and McPherson (2012) who compared four sets of allometric equations i.e. i-Tree Eco, i-Tree Street, CTCC and Urban General Equations and calculated CO_2 storage of Sacramento's urban forest.

The study reported highest estimates by i-Tree Streets (6.41 Mt) and CTCC (6.4 Mt) followed by urban general equations (5.1 Mt) and lowest estimates by i-Tree Eco (4.9 Mt). In both above mentioned studies i-Tree Eco produced the lowest estimates than other methods because in both studies AGB estimates were reduced by applying a correction factor of 0.80 before computing total tree dry weight. i-Tree Eco is designed on the basis of forest grown trees so this correction factor is applied to the open grown trees as they produce less aboveground biomass than forest grown trees (Aguaron & McPherson, 2012; Nowak et al., 2013; Russo et al., 2014). The latest version of i-Tree Eco however considers crown light exposure (CLE) in place of landuse and applies this correction factor to trees with 4 or 5 CLE. This might be one reason for differences in the estimates of HM carbon stock and other studies.

All of the methods used in this study have produced comparable results with relatively minor mean differences which might have arisen from the variation in the input of tree biophysical factors and/or values of coefficients used in allometric equations evaluated in this study. Findings of Huy et al. (2016) also reported dissimilar values of coefficients of allometric equations as one reason for the variation in AGB estimates of broadleaf evergreen forests in Vietnam.

3.5. CONCLUSION

This study conducted in the HM forest reported high tree density and biomass of *O. ferruginea* but at lower DBH and height than *A. modesta*. The study provides first evidence of applicability of existing generic biomass allometric models in the subtropical forest in Pakistan. All of the models used in this study fitted data well but among them the models considering both height and DBH as covariates better predicted total biomass than other (DBH only) based on R^2 adj., RMSE, AIC and BIC values. For *O. ferruginea* both existing models accurately predicted TB when compared to the local equation while in case of *A. modesta* significant underestimation of TB was reported by i-Tree Eco (DBH only model for this species). Considering the multiple criteria (AIC, BIC, R^2 adj. and RMSE) to evaluate the good fit statistics of the existing models against the local equations, the generic pantropical model of Chave *et al.* (2014) was found better predicting TB suggesting its wide applicability and robustness for both deciduous and evergreen species while i-Tree Eco for evergreen species only in subtropical forests in the absence of local allometric equations. The analysis done in this study is helpful in selecting an appropriate biomass model for subtropical region to report carbon stock changes under REDD+.

Chapter 4

ASSESSING THE IMPACT OF LAND USE LAND COVER CHANGE ON REGULATORY ECOSYSTEM SERVICES OF SUBTROPICAL SCRUB FOREST, SOAN VALLEY PAKISTAN

4.1. INTRODUCTION

Forests provide ecosystem services in four domains namely regulatory, provisioning, supporting and cultural services (Baskent, 2020). These services maintain the sustainability of human and ecological communities by providing food, timber, shelter, clean water and air, nutrient cycling, recreation, flood protection and regulate climatic processes (Cheng et al., 2019; Mengist & Soromessa, 2019; Zhao et al., 2019; Baskent, 2020). Forests annually store 2.0 Pg to 3.4 Pg of carbon presenting their considerable role in regulating the regional and global carbon fluxes (Pan et al., 2011). Forests also release annually 1.6 Pg of carbon in to the atmosphere and 12% of these emissions come from forest degradation and deforestation (IPCC, 2014). Developing countries contribute 75% of these CO_2 emissions mainly from land use land cover (LULC) changes induced by socioeconomic activities of adjoining communities (Rodríguez-Echeverry et al., 2018; Trisurat et al., 2019). LULC changes deplete ecosystem carbon storage when forest land is converted to agriculture or other land uses with minimum or no vegetation cover (Xu et al., 2016). However, appropriate forest management practices and implementation of laws restricting human interference maximizes the carbon sequestration potential of terrestrial ecosystems (Kamwi et al., 2017). Hence it is imperative to investigate the spatio-temporal changes in the land cover to understand the carbon sequestration potential of the ecosystem. Remote sensing is a most widely used technique to detect spatial and temporal changes in the forest carbon stock. The information extracted from high resolution satellite data is processed through land cover and ecosystem service models to provide historical trend and future predictions on ecosystem carbon storage. In this study spatio-temporal changes in the vegetation density and carbon stock of the Hayat-ul-Mir (HM) subtropical scrub forest were analyzed under business as usual scenario of land cover changes. The scrub forest in Pakistan shares 19% of the total forested land and contributes 10% of the total forestry emissions due to high rates of

deforestation and degradation (Ministry of Climate Change, 2019). However, the HM is a reserve forest and is under state control, so it was hypothesized that its carbon sequestration potential will increase in future considering the current forest management practices.

4.2. MATERIALS AND METHODS

4.2.1. NDVI classification

Normalized difference vegetation index (NDVI) time series maps (year 2007, 2013 and 2019) were developed in ArcMap (v. 10.2) by measuring the reflectance of red and infrared bands based on density of vegetation using Equation 4.1 (Mohajane et al., 2018). To compare NDVI values, all satellite images (Landsat 7 & 8) were acquired for the same month of the respective years (i.e. October) after monsoon rains when vegetation was stable and also to avoid seasonal variations (Table 4.1). The gap in time of the image acquisition was unavoidable because of cloud cover, image distortion and was also based on availability of satellite data.

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \qquad \text{… Eq. (4.1)}$$

where NIR and RED are the reflectance in near infrared and red bands respectively based on density of vegetation.

Table 4.1: Detail of the satellite imagery downloaded and processed for NDVI and LULC maps

Sr. No.	Satellite/ Sensor	Date of imagery (yyyy/mm/dd)	Path/Row	Resolution (m)	NDVI bands (Red & NIR)
01	Landsat 7 ETM +	2007/10/08	150/37	30	Band 3 & Band 4
02	Landsat 8 (OLI-TRIS)	2013/10/16	150/37	30	Band 4 & Band 5
03	Landsat 8 (OLI-TRIS)	2019/10/17	150/37	30	Band 4 & Band 5

4.2.2. Valuation of ecosystem carbon storage and sequestration services

InVEST (Integrated Valuation of Environmental Services and Tradeoffs) carbon model (v. 3.3.3) was used for the quantification, mapping and valuation of the effect of LULC change on tree carbon storage and sequestration services of the HM forest. The model was fed with LULC raster of the HM forest for year 2019 and carbon data of each LULC class from field estimates of four pools i.e. aboveground, belowground, soil and litter (dead) pool. Carbon storage of the entire study area was estimated by aggregating individual carbon estimates of each LULC class (Equation 4.2 & 4.3). Future LULC raster (for year 2030) was input into the model to predict carbon sequestration (Equation 4.4) in future (Liping et al., 2017). For economic valuation, country specific median price of $36.67/ton of carbon (social cost of carbon) with a discount rate of 2% was used (Ricke et al., 2018). The model resulted in three dimensional estimate of carbon stored and sequestered in each LULC class along with its monetary benefit.

$$C_{m,i,j} = A \times (Ca_{m,i,j} + Cb_{m,i,j} + Cs_{m,i,j} + Cd_{m,i,j}) \quad \text{…Eq. (4.2)}$$

$$C = \sum_{m=1}^{n} C\, m, i, j \quad \text{…Eq. (4.3)}$$

$$S = C^{fut} - C^{cur} \quad \text{…Eq. (4.4)}$$

Where A is the area of grid cell (0.09 ha), $Ca_{m,i,j}$, $Cb_{m,i,j}$, $Cs_{m,i,j}$ and $Cd_{m,i,j}$ refers to the aboveground, belowground, soil and dead (litter) carbon density (Mg/ha) for grid cell (i, j) for land use type (m), C is aggregate carbon density of the ecosystem for current year (C^{cur}) and predicted year (C^{fut}) and S is the carbon sequestration across study area (Liping et al., 2017).

4.2.3. InVEST input data preparation

4.2.3.1. Land use land cover map

To spatially represent forest carbon stock through InVEST carbon model, time series LULC maps of the HM forest were developed. After stacking bands of Landsat satellite images, land use type was categorized into five classes i.e. agriculture, built up area, barren land and *O. ferruginea* and *A. modesta* vegetation based on land uses inside and on the forest boundary. The built up area was represented by shrine of saint

Hayat-ul-Mir and few temporary huts around coal mining sites. Based on spectral reflectance, training sample areas were selected and supervised maximum likelihood classification was done to develop LULC maps of year 2007, 2013 and 2019. Ground truthing was done by creating set of random points and 81%, 83% and 80% classification accuracies were observed for LULC maps of year 2007, 2013 and 2019 respectively.

Prediction of future LULC dynamics for year 2030 was done through CA – Markov modeling under business as usual scenario (BAU). Markov chain analysis is a stochastic modeling approach. It was implemented on time period 2013 to 2019 to create transition areas and transition probability matrix among initial and final states to predict temporal LULC change trends (Equations 4.5 & 4.6). Cellular Automata (CA) model was used for spatial simulations. In CA, each cell decided the data between different states in time for itself and its neighboring cells (through contiguity filter) and decided change in each cell by rules. Weight factor is applied based on proximity of nuclear and neighbor cells which is then combined with transition probabilities to predict state of closer cells so that land use change is not a random decision. A combined CA-Markov model was used to simulate spatio-temporal dynamics among LULC classes using transition probabilities matrix as input to CA model to predict future LULC (Liping et al., 2018; Zhao et al., 2019).

$$P_{ij} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}$$

$$(0 \le Pij < 1 \text{ and } \sum_{j=1}^{n} Pij = 1, i, j = 1, 2, \ldots . n) \quad \text{…Eq. (4.5)}$$

$$S\,(t + 1) = P_{ij} \times S(t) \quad \text{…Eq. (4.6)}$$

Where S is the status of land use at time t and t + 1; and Pij is the transition probability matrix.

Using CA-Markov model in IDRISI Selva (v. 17.0), number of CA iterations was set to 11 as time interval, 5×5 contiguity filter and transition probability matrix (2013 to

2019) was used to predict LULC of 2030. Before running the final model, it was validated by creating prediction map of 2019 from 2007 and 2013 LULC data and then it was compared with real LULC map of 2019 using kappa statistics (Equation 4.7). The LULC maps generated were visualized in ArcGIS (v. 10.2), study area was extracted and converted to InVEST compatible file format before running sequestration and valuation model. LULC change map was also developed using image analysis tool in ArcMap (v. 10.2) to visualize inter-conversion of LULC classes. Complete scheme of study is presented in Figure 4.1.

$$\text{Kappa} = (Po - Pc) / (Pp - Pc) \quad \text{…Eq. (4.7)}$$

where kappa is index to test simulation accuracy; Po, Pc and Pp are the actual, expected and ideal (100%) simulation accuracies respectively (Zhao et al., 2019).

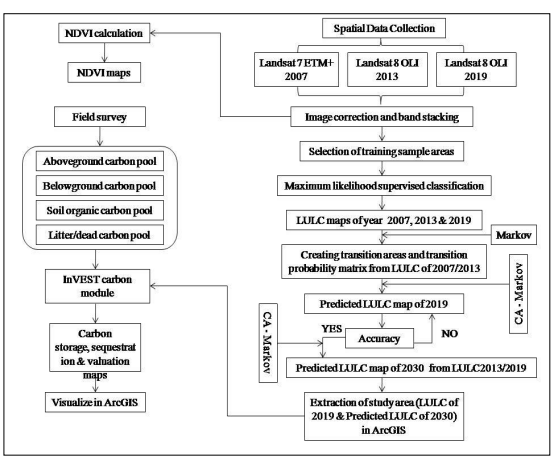

Figure 4.1: Methodology adopted to determine NDVI and to produce LULC and ecosystem service maps

4.2.3.2. Assessment of forest carbon pools

Estimation of biomass carbon stored in the aboveground and belowground parts of *O. ferruginea* and *A. modesta* in the Hayat-ul-Mir forest was done through species specific local allometric equations (Equation 3.3 and 3.4) as described in detail in Chapter 3 (Sub-section 3.2.2.1.).

In the vegetation survey plots (Section 3.2.1. of Chapter 3), subplots of 1m × 1m ($1m^2$) were established in the forest to collect soil and leaf litter samples. For the determination of soil carbon stock, subsurface samples of the soil at a depth of 15 cm were collected after removing surface debris, sealed in polythene bags and were taken to the laboratory for analysis. The samples were first air dried and then passed through a 2 mm mesh to determine soil organic carbon stock (SOCS) through Walkley Black chromic acid wet oxidation method (Walkley, 1947). In this method, 1N $K_2Cr_2O_7$ was reduced by organic carbon compounds in air dry soil sub samples (1 g) and unreduced dichromate was determined by oxidation-reduction titration with 0.5 M $(NH_4)_2SO_4.FeSO_4.6H_2O$ (ferrous ammonium sulfate) solution using diphenylamine indicator. The method gave estimates of both organic matter (OM) and total organic carbon (TOC) in percentage. The SOCS (Mg/ha) was calculated by multiplying the TOC (%) with sampling depth (D) and soil bulk density (BD = 1.62 g/cm^3 for the HM forest) using Equation 4.8 (Tivet et al., 2012).

$$\text{SOCS (Mg/ha)} = \text{TOC (\%)} \times \text{BD (gcm}^{-3}) \times D \quad \text{…Eq. (4.8)}$$

To estimate the carbon stored in the dead fractions, freshly fallen leaf litter was sampled from 1 m^2 subplots. The leaf litter samples were first air dried for two weeks and later litter sub-samples were oven dried at 105°C until a constant mass was attained and litter biomass was calculated following Subedi et al. (2010) using Equation 4.9.

$$\text{Litter Biomass (Mg/ha)} = (W_{field} / A) \times (W_{dry\ sub\text{-}sample} / W_{fresh\ sub\text{-}sample}) \times (1 / 10{,}000) \quad \text{…Eq. (4.9)}$$

Where W_{field} is the wet weight of sample taken from field of area (A) $1m^2$, $W_{dry\ sub\text{-}sample}$ is oven dry weight (g) of sub-sample of litter, and $W_{fresh\ sub\text{-}sample}$ is weight (g) of fresh sub-sample processed to estimate dry weight. Percentage carbon in the leaf litter was determined through loss on ignition method (LOI) by combusting 1 g of oven dried ground litter sub samples at 550°C in a muffle furnace for four hours. The combusted samples were then cooled and weighed to calculate percentage carbon in the leaf litter samples using Equations 4.10 and 4.11 after Allen et al. (1986).

$$\text{Ash (\%)} = (W3 - W1)/(W2 - W1) \times 100 \qquad \text{…. Eq. (4.10)}$$

$$\text{C (\%)} = (100 - \text{Ash}) \times 0.50 \qquad \text{…Eq. (4.11)}$$

Where W1 is weight of crucible (g), W2 is weight of the oven-dried sample + crucible, W3 is the weight of ash + crucible, 0.5 is the factor considering 50% carbon in ash free litter and C (%) is percentage carbon in leaf litter. Litter carbon stock (C_L) was later estimated using Equation 4.12 following Subedi et al. (2010).

$$C_L\ (\text{Mg/ha}) = \text{Litter Biomass} \times \text{\% C} \qquad \text{…Eq. (4.12)}$$

Inverse distance weighted (IDW) interpolation technique in ArcMap was used to estimate carbon density of unmeasured LULC classes (i.e. agriculture, built up area and barren land) in the HM forest. This technique was used as no site specific data was available for these classes in the literature. IDW is a deterministic interpolation technique and is considered most efficient and accurate approach but, it is sensitive to the outliers (Joseph et al., 2010). The maps generated after IDW interpolation are available in Annexure III.

4.2.4. Data Analysis

The data was analyzed using Statistical Package for Social Sciences (SPSS v. 21). Means and standard errors of the carbon stored in each LULC class were computed to compare for the land cover providing maximum carbon storage service.

4.3. RESULTS

4.3.1. NDVI cover

Figure 4.2 presents the NDVI (normalized difference vegetation index) and area covered by each NDVI class from year 2007 to 2019. Based on the NDVI values, total forest area was classified as high vegetation, low vegetation and rock/bare soil. High vegetation (or tree cover) was found to be the most dominant NDVI class. The greenness index of the HM forest increased with time (or forest age) and highest NDVI of 0.68 was calculated for trees covering an area of 1468 ha (89%) in year 2019 compared to NDVI of 0.52 (947 ha) and 0.53 (1061 ha) for the same class in year 2007 and 2013 respectively. Percentage area of the rock/bare soil decreased with time from 150 ha (9%) in year 2007 to 33 ha (2%) in year 2019 with change in NDVI value of – 0.17 to + 0.01 overtime respectively. Change in low vegetation (shrub) cover was also observed from 2007 (555 ha or 34%) to 2019 (152 ha or 9%) and NDVI values varied from 0.19 to 0.24 representing the relative reflectance of red and infrared light.

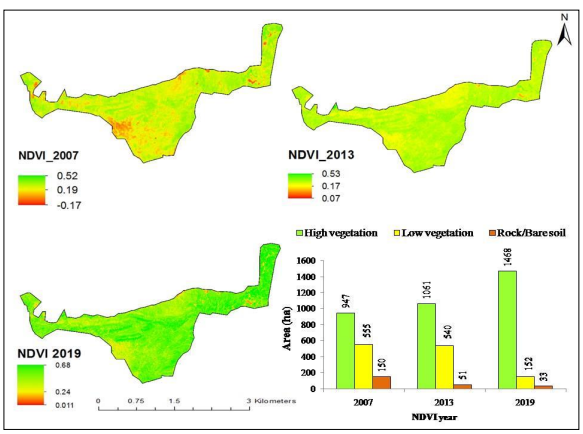

Figure 4.2: Time series analysis and area covered by each NDVI class in the HM forest.

4.3.2. Land cover changes

Spatial and temporal trends in LULC changes during 2007, 2013, 2019 and simulated 2030 (under business as usual scenario) are presented in Figure 4.3 and Table 4.2. Time series analysis showed that vegetation cover of the HM forest comprising of *A. modesta* and *O. ferruginea* gradually increased overtime during 2007 to 2030 decreasing the cover of other LULC classes i.e. agriculture, built up area and barren land. Most of the agriculture (32 ha) and built up area (19 ha) was found on the edges of the forest in 2007 while 81 ha of the land area was barren or not covered with any vegetation and had an irregular spatial distribution. Compared to the BAU 2030 LULC map, 46 ha, 74 ha and 28 ha area of the barren land was decreased during 2007-13, 2007-19 and 2013-2019 respectively. Similar trend in decrease in the agriculture and built up area was observed for the same time frame. There was an overall gain in the area of *A. modesta* and *O. ferruginea* vegetation from 715 ha and

805 ha in year 2007 to 738 ha and 902 ha in the predicted year (2030) due to land cover conversions. The predicted LULC of 2030 represents very low area coverage of agriculture, built up and barren land on the edges of the forest only. Prediction accuracy of the CA-Markov model was found to be 0.84 based on kappa index of agreement between real and simulated LULC of 2019 (Annexure IV).

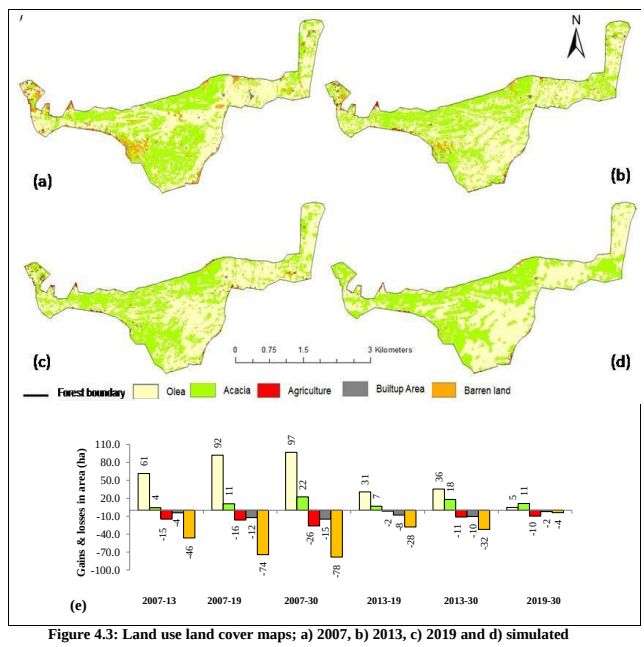

Figure 4.3: Land use land cover maps; a) 2007, b) 2013, c) 2019 and d) simulated BAU 2030 e) gains and losses in area (ha) of LULC classes during 2007 to 2030.

Table 4.2: Area covered by each LULC class in the HM forest during 2007 to 2030

LULC classes	2007		2013		2019		2030	
	Area (ha)	Cover (%)	Area (ha)	Cover (%)	Area (ha)	Cover (%)	Area (ha)	Cover (%)
O. ferruginea	805	48.7	866	52.4	897	54.3	902	54.6
A. modesta	715	43.3	720	43.6	726	44.0	738	44.7
Agriculture	32	1.9	17	1.0	15	0.9	5	0.3
Built up Area	19	1.1	14	0.9	6	0.4	4	0.2
Barren land	81	4.9	35	2.1	7	0.4	3	0.2
Total Area	**1652**	**100**	**1652**	**100**	**1652**	**100**	**1652**	**100**

4.3.3. Carbon storage and sequestration service

In the HM forest, the highest amount of carbon was stored in the bi-climax community of *O. ferruginea* (15.2 ± 1.9 Mg/ha) and *A. modesta* (14.1 ± 1.8 Ma/ha) as AGC, BGC, soil and dead carbon. The limited agriculture activity on the forest boundary was recorded with storing 3.8 ± 0.9 Mg/ha of the carbon whereas least carbon was stored as SOC in the build up and barren LULC classes (Table 4.3).

Table 4.3: Carbon stored (Mg/ha) in the LULC classes of the HM forest in year 2019

LULC class	AGC	BGC	SOC	Dead C	Total C
O. ferruginea	8.7 ± 1.4	1.7 ± 0.02	4.8 ± 0.1	0.023 ± 0.001	15.2 ± 1.9
A. modesta	6.8 ± 1.1	1.4 ± 0.01	5.8 ± 0.4	0.012 ± 0.001	14.1 ± 1.8
Agriculture	1 ± 0.01	0.2 ± 0.001	2.6 ± 0.1	0.003 ± 0.0	3.8 ± 0.9
Built up area	-	-	1.1 ± 0.09	-	1.1 ± 0.09
Barren land	-	-	0.3 ± 0.001	-	0.3 ± 0.001

The Art of writing only for samples use

The InVEST carbon model helped in identifying the LULC which stored and sequestered more carbon than others and had greater potential in provision of this ecosystem service (Annexure V). The tool estimated maximum 15.22 Mg/ha of total carbon stored in the vegetative cover of the forest in the base (2019) and predicted (2030) land covers. However, least carbon was stored (0.33 Mg/ha) in the other land cover classes i.e. agriculture, built-up and barren land suggesting their small contribution in ecosystem carbon storage (Figure 4.4a & 4.4b). Changes or interconversions in LULC classes between base (2019) and predicted (2030) year were detected to determine their benefit and potential for carbon sequestration (Figure 4.4c to 4.4e). It was observed that under BAU scenario, ~14 ha of agriculture and built up area will likely convert into forest vegetation i.e. *A. modesta* and *O. ferruginea* in 2030. The InVEST carbon model predicted highest potential to sequester carbon (14.88 Mg/ha) with net 547 $/ha of monetary benefits for that area. LULC change detection revealed that ~5 ha of agriculture and built up area will become barren in 2030 and additionally 4 ha of vegetative cover will convert to other three LULC classes (agriculture, build up and barren). This interconversions of LULC classes would result in emitting CO_2 instead of carbon sequestration (–12.88 Mg/ha) reducing overall net benefits (–472 $/ha). No change in LULC for 1240 ha of land area was observed for which model did not calculate sequestration rate (SR) and benefits however, interconversions of *A. modesta* and *O. ferruginea* classes was also observed. The InVEST predicted carbon sequestration of 0.66 Mg/ha with a benefit of 24 $/ha at the sites where *O. ferruginea* is expected to replace *A. modesta*. However relatively lower carbon sequestration is expected at sites where *A. modesta* would replace *O. ferruginea* in future. Cumulatively, the model calculated 23912.18 Mg and 24024.09 Mg of carbon stored in the HM forest currently (2019) and in future (2030) respectively and 111.91 Mg of carbon sequestered with net present value (benefit) of $4112.05 at a discount rate of 2%.

The Art of writing only for samples use

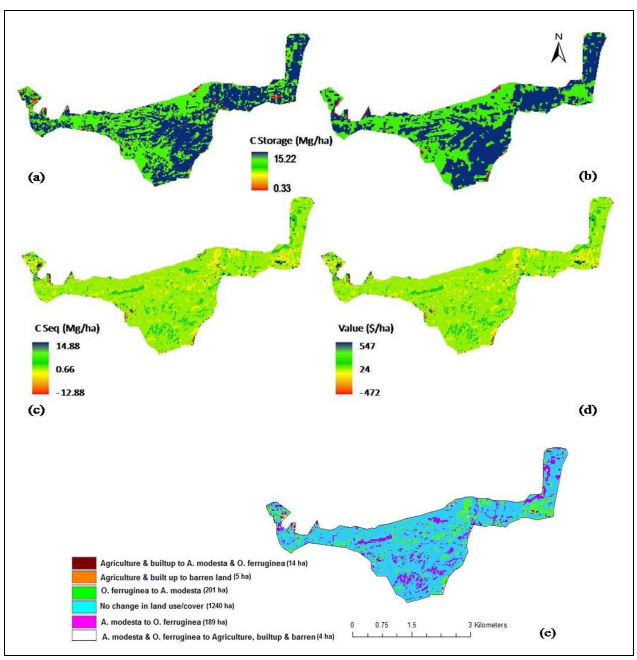

Figure 4.4: Spatial distribution of ecosystem carbon storage a) in 2019 b) in 2030, c) carbon sequestration d) economic value in the HM forest and e) LULC changes during 2019 to 2030.

The Art of writing only for samples use

4.4. DISCUSSION

Current study presents modeling based prediction of the land cover changes and their effects on provision of regulatory ecosystem service of the HM forest. The study site is under jurisdiction of provincial government and is a declared reserve forest under Punjab Forest (Amendment) Act 2010. The act prohibits any cultivation, land clearings, grazing, mining and timber harvesting unless granted under limited rights (Government of Punjab, 2010). Therefore, limited human activity was observed in the HM reserve forest in the form of some agricultural activity and built up area on forest edges only. Barren land (area with no vegetative cover) was seen throughout the forest, but it declined and was replaced with tree cover overtime (2007 to 2019) as also represented through NDVI.

NDVI helped in investigating density and health of the forest on spatio-temporal basis. The most dominant cover class in the HM forest was made by the bi-climax community of *O. ferruginea* and *A. modesta* represented with an increase in NDVI value overtime. The limited human activity in HM reserve subtropical forest resulted in increase (~32%) in its vegetation density and perhaps its biomass carbon stock during 2007 to 2019. Reason for this increase in the vegetation density can be attributed to the implementation of Punjab Forest (Amendment) Act 2010. The sub-section 1 through 4 of section 26 of the act defines rights and penalties to restrict human interference in the reserve forests. The act restricts all kinds of human activities including encroachments, construction, timber and fuelwood harvesting, damage to soil and natural vegetation, cattle grazing and trespassing and any kind of land use change other than for the conservation purpose. The act also revised penalties to offences in the form of imprisonment for six months or fine ranging between ten thousand PKR to 0.5 million PKR or both depending on the worth of damage which could double if offence is committed after sunset (Government of Punjab, 2010). Consistent to the findings of present study, Kamwi et al. (2017) also reported increase in the forest cover of protected and communal areas of Zambezi region in Namibia during 1991-2010 after the implementation of forest policy restricting any human interference in the region. Contrary to the current study, Negassa et al. (2020) reported 37.4% decline in the forest area due to agricultural expansions (34%) in

Komto protected forest of Ethiopia due to lack of forest policy and participatory forest management practices.

Other reason for increase in the vegetated cover of HM forest is related to significant reduction in the livestock grazing during the last 10 years due to shift to non-livestock dependent livelihood practices of the adjacent communities. Significant increase in the number of factories from just 28 in year 2007 to 145 in year 2019 has been observed in the district. There was also significant increase in the available agriculture machinery which reduced dependence on work animals (Government of Punjab, 2007, 2013, 2019). The decrease in grazing pressure provided relief to the scrub forest vegetation (both shrubs and climax species) and it restored as reflected in the NDVI and LULC for year 2013 and 2019. Findings of this study are contrary to Mannan et al. (2019) reporting decrease in vegetation cover with lower NDVI values (1998 to 2018) for *A. modesta, O. ferruginea, Ziziphus spp.* and *Pinus spp*. dominated subtropical forest in Himalayas, Pakistan due to increase in urbanization and human interferences in the area.

In the current study, with continued forest management practices and decreased grazing pressure, the cover of both *A. modesta* and *O. ferruginea* is expected to further increase under BAU scenario replacing agriculture, built up and barren land covers as represented in simulated LULC of 2030. The shrine of Hayat-ul-Mir (representing some built up area) will remain in place as it provides spiritual and cultural ecosystem services to the nearby communities of Kalial, Biyak and Khurra villages.

Apart from the land cover changes, other factors such as rising atmospheric CO_2 concentration at a rate of 2.5 ppm/year (expected 438 ppm in 2030) might induce a fertilization effect enhancing the growth of plant communities (Dunn et al., 2020). But, coupled with the elevated CO_2 levels, future warming and change in precipitation could limit the stem and root growth along with an increase in soil respiration (Gray & Brady, 2016). The current pace of global warming has already caused 1°C rise in temperature over the last 40 years in Pakistan and decreased precipitation in the Soan valley, the future warmer climate with elevated CO_2 concentration might result in some decrease in ecosystem productivity (Bibi et al., 2014; Chaudhry, 2017). But the

model was limited in simulating the effect of climatic variability on land cover of the forest.

Gradual increase in tree cover during 2007 to 2019 and simulation for 2030 implies accumulation of biomass and thus higher carbon storage and sequestration potential of the HM forest in the future. The order of carbon stored in the HM forest was as; aboveground > soil > belowground > dead pools. The aboveground vegetation was identified as the largest pool storing carbon. Major contribution was made by *O. ferruginea* (23.8 Mg/ha) but comparatively the estimates were lower than Sohawa (25.3 Mg/ha) and Himalayan (68.9 Mg/ha) subtropical forests of Pakistan (Nizami 2012; Shaheen et al., 2016). The estimates of soil carbon density of the current study (3.69 Mg/ha) are higher than those reported for Sohawa subtropical forest (2.54 Mg/ha) representing its significance in storing carbon for long term if undisturbed (Nizami 2012).

The biophysical assessment of tree carbon stock showed that the subtropical broadleaved evergreen species (*O. ferruginea*) stored more carbon than subtropical broadleaved deciduous species (*A. modesta*) in the HM forest reserve. This interspecific difference suggests the relative importance and potential of both species in carbon sequestration as indicated through the InVEST carbon model. Similar trend in relative carbon storage and sequestration was reported by Arunyawat and Shrestha (2016) for deciduous and evergreen plantations in Northern Thailand. The ecosystem service assessment presented an increase in carbon storage in the HM forest in the future under BAU scenario which is consistent to the findings of Sil et al. (2017) and Zhao et al. (2019) for the simulated period in the river basins in Portugal and China respectively. Carbon storage was found comparatively high at the sites of evergreen species than where deciduous species is distributed in the HM forest whereas least carbon storage in the non-vegetated classes in the base and predicted year. The historical trend in the relative area coverage of both species during 2007 to 2019 and predicted LULC presented *O. ferruginea* dominating the *A. modesta*. This analysis suggests that under a future warmer climate the evergreen species will have more potential in mitigating climate change. This analysis is also helpful in identifying areas of potential carbon storage and where to implement management interventions to increase the service of tree carbon sequestration.

The analysis also revealed a large area of the forest (75%) where no change in land cover is expected during 2019 to 2030. The simplified carbon cycle in the InVEST did not calculate sequestration rate (SR) for that area during base and predicted year. Therefore the model resulted in a low sequestration estimate of 111.91 Mg C (or 0.006 Mg C/ha/yr) during 2019 to 2030 for the remaining land area (25%) which is expected to undergo LULC change. Consistent to the present study, Zhao et al. (2019) also reported low sequestration rates due to model limitations.

The analysis also identified sites with negative sequestration rates where loss of stored carbon (as CO_2 emissions) is expected to occur due to conversion of vegetated land to built up or barren area in future. Additionally, low SR was calculated for the land cover class where area under *O. ferruginea* is expected to be replaced by *A. modesta* on lower elevations. The low SR for this conversion is related to a relatively low potential of *A. modesta* (deciduous) to store carbon than *O. ferruginea* (evergreen) and InVEST assumed it as some loss of stored carbon. Increase in the service of carbon sequestration was observed where *A. modesta* is expected to be replaced by *O. ferruginea* on higher elevations in the future. The SR was highest for the pixels where agriculture, built up and barren area are expected to convert to forest vegetation.

Considering the intensity of LULC change in the HM forest, SR was low compared to the other studies. Sil et al. (2017) reported higher SR (1.63 Mg/ha/yr) under projected (2020) forest expansion scenario in the Sabor river basin landscape in Portugal due to 50% increase in broadleaved, chestnut and coniferous forests. The difference in the estimates of both studies is related to the type and percentage area of LULC converted and site climatic factors affecting plant growth. Compared to current study, Zhao et al. (2019) predicted 16% of the land area of the Heihe river basin in China to be converted into other land uses in 2029 reducing the carbon density where shrub land was expected to convert to grassland and grassland into bare land. Leh et al. (2013) also documented decrease in ecosystem carbon storage and sequestration service during 2000 to 2009 from LULC change in West Africa. Carbon density in a forest does not remain constant, but it is high during its full vigor growth phase and falls with tree age and thus also affects carbon additions to soil from litter production. Increase in site productivity by implementation of management interventions also improves ecosystem potential of carbon storage and sequestration (Sing et al., 2018). Thus the oversimplification of the carbon cycle in InVEST model and assumption of

zero SR where no LULC change is observed might lead to some misrepresentation of actual supply of this ecosystem service.

Like carbon SR, gains and losses in the economic value of ecosystem service was observed for the type of LULC converted during 2019 to 2030. The monetary benefit of carbon sequestration is expected to be highest at the sites where non-vegetated cover classes might convert into *O. ferruginea* and *A. modesta* and decrease in the value where the forest cover is expected to be replaced with barren land. The net present value (NPV) of carbon sequestered in the current and future land covers ($4112 or PKR. 0.66 million only) of the HM forest was low because of LULC change in 25% of the land area only and limitation of the model to calculate NPV of remaining 75% of the intact area. The monetary value of this ecosystem service is difficult to be compared with other studies due to the difference in currency units, the social cost of carbon (SCC) and discount rate reflecting society's preference for immediate benefits of carbon sequestration over future benefits. Contrary to the findings of this study, Sil et al. (2017) with SCC of $ 23, $ 44 and $ 312 (at a discount rate of 1, 3 and 7%) reported a significantly high value of this ecosystem service from ~50% change in LULC under future scenario. Together with the estimates of carbon storage and sequestration, the economic valuation of this service can help in identifying the areas of potential carbon sequestration to maximize the net benefits of forest management interventions.

4.5. CONCLUSION

The current study reveals that land cover changes have occurred in the Hayat-ul-Mir forest during past decade. During 2007 to 2019, the land covers of *A. modesta* and *O. ferruginea* were increased and are further expected to increase in the simulated period (year 2030) based on BAU scenario. The current livelihood practices of the community and restrictions imposed by the act were found satisfactory in reducing human impact. However, limited agricultural activity on the forest edges was observed but in the declining trend. Built up and barren land area covers also decreased overtime and most of these classes were represented around coal mining sites and shrine during current and simulated land covers. The biophysical and economic assessment of the service suggested increase in future carbon storage with current management practices. The InVEST model was limited in the assessment of

carbon sequestration and did not calculate it for the area which is expected to remain same in 2030. This might had lead to some misrepresentation of actual carbon sequestration potential and net benefits of the HM forest. Improvements in the model are therefore required to accurately account for the carbon sequestration rates. Some interconversions of the LULC classes were also observed for the simulated land cover (year 2030) where the vegetation might replace other land uses (such as agriculture, build up and barren). For those parcels of land, such interconversions would bring positive impact in terms of carbon storage. The model estimated negative rates for areas where termination of agriculture and mining activity (representing some built up area) would make land vacant. CO_2 emissions are expected from those land parcels if not restored with native vegetation. Hence based on this analysis, the study provides a valuable input to inspect the locations that are worse off and where appropriate management interventions must be introduced to increase the forest carbon storage and sequestration.

Chapter 5

EFFECT OF CLIMATIC FACTORS ON LEAF LITTER DECOMPOSITION DYNAMICS OF A SUBTROPICAL SCRUB FOREST IN PAKISTAN

5.1. INTRODUCTION

Precipitation and temperature are the two driving factors that regulate nutrient cycling and soil carbon storage in the terrestrial ecosystems. But disturbance in these factors due to climatic changes has been reported to cause shifts in the rate of litter decomposition affecting carbon balance of the ecosystems (Gregorich et al., 2017; Stuble et al., 2019). Litter decomposition is an important ecosystem service that maintains the flow of nutrients for ecosystem productivity. However, acceleration in the pace of decomposition leads to positive feedback to climate change. Climatic warming and altered moisture regimes affect litter quality, microbial community composition and their enzyme activity causing shifts in the rate of cycling (Petraglia et al., 2018). Studies from tropics, subtropics and temperate regions have reported increase in the pace of litter decomposition and significant efflux of CO_2 from microbial (soil) respiration under warming (Innangi et al., 2015; Gregorich et al., 2017; Yu et al., 2019; Stuble et al., 2019; Chuckran et al., 2020). Pakistan comprises of diverse forest ecosystems but an unprecedented rise of 0.6ºC to 1ºC temperature in hyper arid and mountain regions of the country over last 40 years might have already affected ecosystem functions (e.g. terrestrial carbon cycle). It is expected that the predicted rise of 2.3ºC to 4.5ºC in temperature and increase in precipitation in Pakistan might further deteriorate ecosystem services. But no such studies investigating impacts of predicted warming and precipitation changes on litter decomposition and carbon turnover have been made in Pakistan. So this study was designed to investigate the effect of predicted climatic warming and increase in soil moisture on litter decomposition dynamics of the Hayat-ul-Mir forest. It was hypothesized that warming and higher moisture availability will accelerate the pace of decomposition with fast carbon mineralization and soil CO_2 efflux in the microcosm conditions. This study was designed to provide experiment based estimation to accurately highlight the influence of climatic warming and increase in precipitation on nutrient cycling and carbon balance of the subtropical scrub forest.

5.2. MATERIALS AND METHODS

Litter bag technique was used to assess the dynamics of leaf litter decomposition and two experiments were designed as follows;

- Field incubation experiment in the Hayat-ul-Mir (HM) forest
- Laboratory microcosm incubation experiment under elevated temperature and soil moisture conditions

To carry both experiments following methodology was adopted.

5.2.1. Leaf litter collection and sample processing

Freshly fallen mixed species leaf litter was collected from the forest floor in the month of March 2018 after establishing 47 survey plots of 1 m × 1 m area in the forest. The plots were established at sufficient distance (~2 km) from each other to get a complete representation of the forest eliminating any site differences due to variable topography (Figure 5.1). The leaf litter collected was comprising of newly shed leaves of climax community of *A. modesta* and *O. ferruginea* along with leaf litter of *Prospois juliflora* (invasive species) and shrubs (*Justicia adhathoda, Dodonea viscosa*, *Buxus sp*. and *Maytinus sp*.) as none of the survey plot was purely comprising of bi-climax community. The collected samples of leaf litter were transported to the laboratory, were air dried for one week and then oven dried at 60ºC to constant weight and were sealed in plastic bags till further processing. From the dried litter, subsamples (from each plot) were analyzed for their carbon content (%) through Loss on Ignition method after combusting 1g of leaf litter at 550ºC for 4 hours in a muffle furnace following Allen et al. (1986).

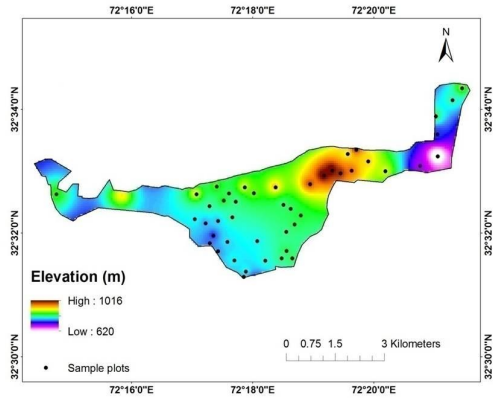

Figure 5.1: Spatial distribution of survey plots taken in the HM forest for the collection of leaf litter

5.2.2. Preparation of litter bags

Litter bag technique was used to monitor the decomposition process during field and laboratory incubation experiments. Litter bags (LBs) of nylon (15cm × 15cm) with a mesh size of 1.5 mm^2 were filled with 5g (±0.01) of dried mixed species leaf litter. The pore size of bags was kept sufficiently smaller to allow for proper soil (containing diverse microbial communities) and litter interaction during decomposition. The pore size also prevented any losses of smaller leaves or twigs and restricted entry of the mesofauna into the liter bags (Innangi et al., 2015). Litter bags for both experiments were prepared in the same manner.

5.2.3. Field incubation experiment

To assess litter decomposition dynamics in the field, two elevation ranges i.e. $E_{(600-850\ m)}$ and $E_{(850-1020\ m)}$ at sufficient distance from each other were selected in the HM forest (Figure 5.2). In the forest soil (10-15 cm depth), 102 LBs containing mixed

species leaf litter were incubated and were covered with litter from forest floor. Of the six incubation sites, each received 17 replicate LBs from which three bags per incubation site were taken at each of the four harvest intervals. Extra bags were incubated to compensate for the losses due to physical damage during extraction of bags at the time of harvest or others. All the incubation sites were marked and their geographic position was also noted. The field incubation experiment continued between May 2018 to May 2019 and replicate bags were harvested four times after 90, 180, 270 and 360 days of decomposition in the months of August, November 2018 and February, May 2019. During field experiment, mean soil moisture remained 15.16 ± 1.3% at the incubation sites and the soil had silty clay loam texture. The ambient temperature varied between 12°C (min.) and 35°C (max.) with 30.63 ± 5.5 mm/mo precipitation and mean 60% relative humidity was recorded during study period (Figure 5.3).

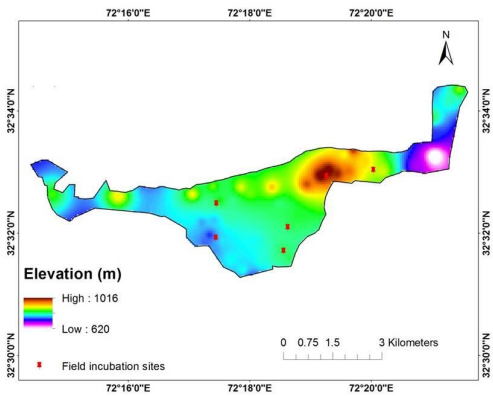

Figure 5.2: Spatial distribution of field incubation sites for litter decomposition at various elevations in the HM forest

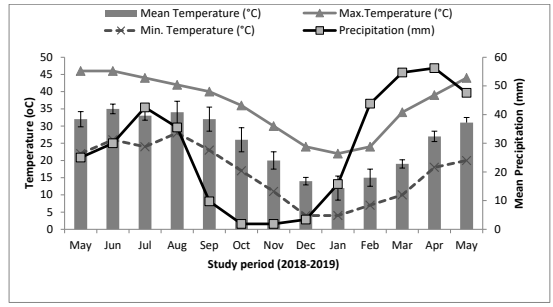

Figure 5.3: Variation in temperature and precipitation during field experiment

5.2.4. Laboratory microcosm incubation experiment

Laboratory microcosm incubation experiment was done to assess the rate of leaf litter decomposition under projected increase in temperature and precipitation by year 2100 for Pakistan. To construct microcosms, soil was collected (at random) from the HM forest at a depth of 15 cm. It was mixed carefully to get complete representation of the soil microbial flora from all sampling sites before starting decomposition experiment. The composite mixture of soil (un-sieved) was pre-incubated at 24°C and 15% soil moisture to keep microbial communities alive and acclimatize before starting experiment following Innangi et al. (2015).

Microcosms were constructed by taking six plastic boxes (320 × 260 × 100 mm) in which nine replicate LBs/box were placed on 10 cm thick layer of pre-incubated soil and covered with additional layer of soil and litter material on top to mimic field conditions. The experiment was a factorial design with three temperature and two soil moisture treatments (9 LBs × 3 temperature × 2 soil moisture).

The microcosms were kept in the Plant Growth Chamber (WGC-450) at ambient (T_o) HM conditions (24.6°C/18°C day/night) based on 5 years metrological record and at two warming treatments i.e. T_o + 2.3°C (or 26.9°C/20.3°C) and T_o + 4.5°C (or 29.1°C/22.5°C) to simulate low (RCP 2.6) and high emission (RCP 8.5) scenario of IPCC respectively (Cruz et al., 2007; Chaudhry, 2017). Two replicate microcosms per

temperature treatment (T_o, T_o + 2.3°C and T_o + 4.5°C) were established in the plant growth chamber in a way that one replicate was maintained at 15% (control) and other at 20% (elevated) of gravimetric soil moisture. Relative humidity during whole experiment was maintained at 60% and replicate litter bags were harvested after 30, 60 and 90 days of incubation.

5.2.4.1. CO_2 evolution from soil respiration

CO_2 evolved from soil respiration during microcosm experiment was analyzed three times during decomposition (i.e. after 30, 60 and 90 days). The CO_2 evolved was trapped in 20 ml of 1M NaOH exposed to experimental conditions for 24 hours. The carbonates formed in alkali solution (NaOH) were precipitated with 3M $BaCl_2$ and the un-reacted alkali was titrated with 1M HCl using phenolphthalein as indicator. The amount of soil respiration or CO_2 (mg/day) evolved was computed using Equation 5.1 (Anderson, 1982).

$$CO_2 = (B - V)\ NE \qquad \text{....Eq. (5.1)}$$

Where B is the volume of acid used to titrate blank, V is the volume of acid used to titrate un-reacted NaOH after trapping CO_2, N is the normality of acid and E is the equivalent weight of CO_2 i.e. 22.

5.2.5. Leaf litter decomposition dynamics

5.2.5.1. Litter mass loss and carbon: nitrogen ratio

Harvested LBs from field and laboratory microcosms were carefully opened and excess soil particles were removed with the help of a soft brush. The decaying litter was oven dried at 75°C to constant mass and percentage mass loss was calculated following Equation 5.2 (Kurz-Besson et al. 2005).

$$\text{Mass Loss (\%)} = [(l_o - l_t) / l_o] \times 100 \qquad \text{....Eq. (5.2)}$$

Where l_o is initial mass, l_t is the mass of litter in the bag after decomposition at interval of *t* time. The percentage residual weight (RW) of decaying litter was calculated using equation 5.3 (Saura-Mas et al., 2012).

$$RW\ (\%) = l_t / l_o \times 100 \qquad \text{....Eq. (5.3)}$$

The percentage of carbon remaining (C) in the decaying leaf litter was determined through Loss on Ignition Method (Allen et al., 1986) as a measure of carbon mineralization. Litter nitrogen (N) was estimated after treating samples with concentrated H_2SO_4 in the presence of Kjeldahl catalysts (K_2SO_4 – $CuSO_4.5H_2O$ – Se). Digested samples were distilled in the presence of 10N NaOH. The ammonia trapped in 0.1N H_3BO_3 was titrated with 0.01N H_2SO_4 (Muñoz-Huerta et al., 2013). Litter carbon and nitrogen ratio (C:N) was then calculated.

Single exponential model of Olson (1963) was used to evaluate trends of decomposition. The model suggests a fast nutrient regulated initial decomposition stage linked to leaching and degradation of easily degradable soluble compounds and carbon sources (labile fractions). The later stages are associated with lignin and nitrogen decomposition (recalcitrant fractions) until a stable phase is reached. Based on Olson model the decomposition constant (k yr^{-1}) was computed using Equation 5.4 following Innangi et al. (2015).

$$k = -(\ln (l_t / l_o) \times 1 / t_i) \qquad \text{.... Eq. (5.4)}$$

where l_o is the litter mass present in the beginning of incubation period (at time t_o) and l_t is the mass at the end of incubation period and t_i is the days of decomposition. The Olson (1963) kinetics model was also used to compute litter half life ($T_{50\%}$) which is the estimated time required to decompose 50% of the litter mass using Equations 5.5 (Wang et al., 2009).

$$T_{50\%}\ \text{(days)} = 0.693/k \qquad \text{..... Eq. (5.5)}$$

5.2.6. Data analysis

Data analysis was done using SPSS (v.21). Descriptive statistics was used to compute means of parameters investigated to report litter decomposition dynamics. Bivariate correlation analysis was done to check the effect of elevation on litter decomposition. One way ANOVA was run to find the effect of incubation time on litter decomposition in the field. Three way ANOVA with Tukey HSD test was used to check the main effects and interactions of independent variables (incubation temperature, time and soil moisture) on litter decomposition in the microcosms. Multiple comparisons were made to identify the treatments that were significantly

different from each other. Multiple regression analysis was used to analyze the percentage variance in parameters of litter decomposition under the influence of predictor variables (i.e. treatment conditions).

5.3. RESULTS

5.3.1. Litter decomposition dynamics in the Field

Figure 5.4 presents the effect of site elevation on mean litter mass loss and residual weight. Comparatively, higher mean litter mass loss was observed at E $_{(600\text{-}850\ m)}$ (38.9 ± 2.2%) with corresponding lower residual weight (61.1 ± 1.1%) than at E $_{(850\text{-}1020\ m)}$ with 28.3 ± 0.7% mass loss and 71.7 ± 0.8% residual weight during field experiment.

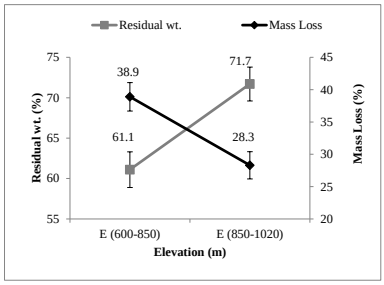

Figure 5.4: Effect of site elevation on litter mass loss and residual weight in the field

Figure 5.5 presents the effect of site elevation on litter decay rate (k yr^{-1}) and half life ($T_{50\%}$). Comparatively high litter decay rate (k yr^{-1}) of 0.931 ± 0.01 with corresponding low half life (0.92 ± 0.02 yr) was recorded at E $_{(600\text{-}850\ m)}$ compared to E $_{(850\text{-}1020\ m)}$ site with k (0.586 ± 0.01) and $T_{50\%}$ (1.37 ± 0.03 yr) during field decomposition experiment.

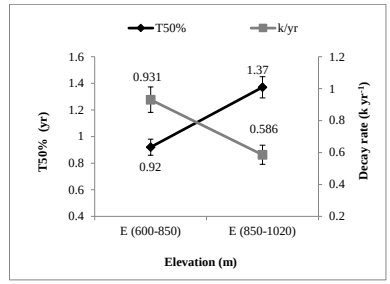

Figure 5.5: Effect of site elevation on litter half life and decay rate in the field

Effect of site elevation on litter remaining elemental concentration (C, N and C:N) is presented in Figure 5.6. Comparatively low remaining C (14.2 ± 0.6%), N (1.196 ± 0.01%) and C:N (11.8 ± 0.4) were observed at low elevation i.e. E $_{(600\text{-}850\ m)}$ compared to E $_{(850\text{-}1020\ m)}$ recorded with 18.1 ± 0.7% of C, 1.304 ± 0.01% of N and 13.7 ± 0.4 C:N.

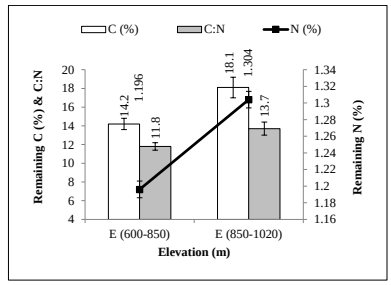

Figure 5.6: Effect of site elevation on litter remaining elemental concentration

Table 5.1 presents the Bivariate correlation analysis of the effect of elevation on litter decomposition dynamics in the field. A negatively significant correlation ($p < 0.05$) was found between elevation and litter decay rate however it was positively significant ($p < 0.05$) between elevation and litter half life. No significant correlation was found between elevation and mass loss, residual weight, litter C, N and C:N. A negatively significant correlation was also found between mass loss and litter C, N ($p < 0.01$) and C:N ($p < 0.05$).

Table 5.1: Correlation analysis of site elevation with litter decomposition dynamics

Parameters	Elevation (m)	Mass loss (%)	Residual wt. (%)	k (yr^{-1})	$T_{50\%}$ (yr)	C (%)	N (%)
Elevation (m)	1						
Mass Loss (%)	-0.368	1					
Residual wt. (%)	0.368	-1.000**	1				
k (yr^{-1})	-0.495*	0.334	-0.334	1			
$T_{50\%}$ (yr)	0.481*	-0.391	0.391	-0.903**	1		
C (%)	0.382	-0.706**	0.706**	-0.014	0.141	1	
N (%)	0.366	-0.777**	0.777**	0.047	0.025	0.775**	1
C:N	0.271	-0.485*	0.485*	-0.030	0.177	0.907**	0.441*

** $p < 0.01$, * $p < 0.05$

One way ANOVA showed significant effect of incubation time on litter mass loss and residual weight (F = 9.029, $p < 0.01$), remaining C (F =7.203, $p < 0.01$) and N (F = 22.305, $p < 0.001$). No significant effect of incubation time was observed on litter decay rate (F = 1.719, $p = 0.195$), half life (F = 2.306, $p = 0.108$) and C:N (F = 2.498, $p = 0.089$) (Table 5.2).

Table 5.2: One Way Analysis of Variance (ANOVA) showing effect of incubation time on litter decomposition dynamics in the field

Variable	Sum of squares	df	Mean square	F	Sig.
Mass Loss (%)	2658.6	3	886.2	9.029	0.001
Residual wt. (%)	2659.2	3	886.4	9.029	0.001
k (yr^{-1})	0.502	3	0.167	1.719	0.195
$T_{50\%}$ (yr)	137184.3	3	45728.1	2.306	0.108
C (%)	156.9	3	52.315	7.203	0.002
N (%)	0.328	3	0.109	22.305	0.000
C:N	25.23	3	8.411	2.498	0.089

Significant difference ($p < 0.01$) in the mean litter mass loss and residual weight was observed between 90 and 360 days of field incubation. Highest mass loss (51.48 ± 3.6%) and low residual weight (48.51 ± 3.6%) was observed after 360 days of decomposition compared to the initial rate after 90 days (22.1 ± 2.1% and 77.9 ± 2.1%). Comparatively low rate of litter mass loss was observed after 180 and 270 days of incubation (Figure 5.7).