Climate change impacts: In the perspective of soil organic carbon, above-ground biomass and vegetation shifts (A case study from Nepal)

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Dedications

This PhD thesis is dedicated to my late father Mr. Ratna Bahadur Malla. His fatherly love and support have always remained magnificent.

Eidesstattliche Versicherung

Declaration

Hiermit erkläre ich an Eides statt, dass ich die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

I hereby declare, on oath, that I have written the present dissertation by my own and have not used other than the acknowledged resources and aids.

Hamburg, 15.12.2023 (Rajesh Malla)

Summary

Climate change impact has been examined with regard to different aspects of forest ecosystems such as soil organic carbon (SOC), above-ground tree biomass (AGTB) and vegetation shift (broad-leaved and coniferous forests). The SOC and AGTB were assessed in terms of their change in amount with future climate change whereas vegetation shift was assessed in terms of shifting altitudinal ranges, natural habitat area and species in future climate change. Nepal was selected as a test region to study the impact of climate change on these aspects due to the large differences in altitude and temperature in the country and also it is one of the most vulnerable countries to climate change.. The objectives of this study were, i.e. 1) Are climatic variables important for the estimation of SOC and AGTB? 2) Does future climate change contribute to an increase in SOC and AGTB stock in the forest ecosystem? 3) Does climate change affect the vegetation shift? Multiple linear regression, Random forest and Maximum Entropy (MaxEnt) models were applied to investigate the objectives. The availability of forest resource assessment (2010-2014) data of Nepal, accompanied by topographic and bioclimatic variables, provided the opportunity to study the impacts of climate change on forest ecosystems at a national scale

Climatic variables (temperature and precipitation) show a strong relation with SOC and AGTB. The climatic variables do not only explain SOC and AGTB at present, but they can also predict SOC and AGTB under future climate change scenarios. This study found a higher amount of SOC existed at higher altitudes compared to lower altitudes and the rate of accumulation of SOC increasing at a higher rate with the increase in altitude. The lower latitude has a higher temperature and vice versa. In the projected climate change scenario, i.e. CMIP6, SSP2 4.5 for 2040-2060, the amount of SOC was found to decrease by 3.85% in general with the increasing temperature and precipitation against near current period (1970-2000). In Contrast, the study indicated a positive relation between climatic variables (temperature and precipitation) and AGTB that found the amount of AGTB to increase by 2.96% in general in the same projected climate change scenario against same near current period. Moreover, vegetation shifts from one forest to another are likely to occur over a longer period, influenced by climatic variables. This study found the vegetation shift in terms of areas, i.e. coniferous to broad-leaved forests (1579 km^2) and its reverse (232 km^2), in terms of altitudinal shift, i.e. 77m higher for broad-leaved forests and 54m lower for coniferous

forests, and in terms of species, i.e. broad-leaved forests to coniferous forests and its reverse in the future climate change scenario.

The result confirms that a higher amount of SOC stock exists in the forests at a higher altitude compared to the forests at lower altitude. However, the amount of SOC is likely to decrease while the amount of AGTB is likely to increase in the future climate change scenarios. Moreover, the result shows that vegetation shift from coniferous to broad-leaved forest is more dominant than the broad-leaved to coniferous forests and the area of broad-leaved forest will likely to expand while the area of coniferous forest is likely to shrink in the future climate change scenario.

Therefore, this study highlights the need to retain SOC amount thus reducing carbon emission from the soil. It also highlights the significance of, particularly, high altitude forest in sequestrating atmospheric carbon in the future climate change scenario. Moreover, the study highlights that the expansion of broad-leaved forests due to vegetation shift may benefit in terms of species diversity, SOC amount and forest resilience and also may affect coniferous forest- dependent people and enterprise due to lower supply of the forest products. Thus, the study suggests to adopt sustainable management of high altitude forests to increase mitigation potential of the forests (increase carbon sequestration and reduce carbon emission) and also suggests to assess adaptation measures for vulnerable communities due to climate change.

Zusammenfassung

Die Auswirkungen des Klimawandels wurden im Hinblick auf verschiedene Aspekte von Waldökosystemen wie organischer Kohlenstoff im Boden (SOC), oberirdische Baumbiomasse (AGTB) und Vegetationsverschiebung (Laub- und Nadelwälder) untersucht. Der SOC und die AGTB wurden im Hinblick auf ihre Veränderung bei künftigen Klimaänderungen bewertet, während die Vegetationsverschiebung im Hinblick auf die Verschiebung der Höhenlagen, der natürlichen Lebensraumfläche und der Arten bei künftigen Klimaänderungen bewertet wurde. Nepal wurde als Testregion ausgewählt, um die Auswirkungen des Klimawandels auf diese Aspekte zu untersuchen, da das Land große Höhen- und Temperaturunterschiede aufweist und außerdem eines der am stärksten vom Klimawandel betroffenen Länder ist. Die Ziele dieser Studie waren: 1) Sind klimatische Variablen wichtig für die Schätzung von SOC und AGTB? 2) Trägt der zukünftige Klimawandel zu einem Anstieg des SOC- und AGTB-Bestandes im Waldökosystem bei? 3) Wirkt sich der Klimawandel auf die Vegetationsverschiebung aus? Zur Untersuchung der Ziele wurden multiple lineare Regression, Random Forest und MaxEnt-Modelle verwendet. Die Verfügbarkeit von Daten der nepalesischen Waldressourcenerhebung (2010-2014) in Verbindung mit topografischen und bioklimatischen Variablen bot die Möglichkeit, die Auswirkungen des Klimawandels auf Waldökosysteme auf nationaler Ebene zu untersuchen

Klimavariablen (Temperatur und Niederschlag) zeigen eine starke Beziehung zu SOC und AGTB. Die Klimavariablen erklären nicht nur den derzeitigen SOC und AGTB, sondern sie können auch den SOC und AGTB unter zukünftigen Klimawandelszenarien vorhersagen. In dieser Studie wurde festgestellt, dass in höheren Lagen eine größere Menge an SOC vorhanden ist als in niedrigeren Lagen und dass die SOC-Akkumulationsrate mit zunehmender Höhe stärker ansteigt. Der niedrigere Breitengrad hat eine höhere Temperatur und umgekehrt. Im projizierten Klimawandelszenario, d.h. CMIP6, SSP2 4.5 für 2040-2060, wurde festgestellt, dass die Menge an SOC im Allgemeinen mit der steigenden Temperatur und dem zunehmenden Niederschlag im Vergleich zum nahen aktuellen Zeitraum (1970-2000) um 3,85 % abnimmt. Im Gegensatz dazu wies die Studie auf eine positive Beziehung zwischen den klimatischen Variablen (Temperatur und Niederschlag) und der AGTB hin, die ergab, dass die Menge der AGTB in demselben prognostizierten Klimawandelszenario im Vergleich zum nahen aktuellen Zeitraum im

Allgemeinen um 2,96 % zunimmt. Darüber hinaus ist es wahrscheinlich, dass Vegetationsverschiebungen von einem Wald in einen anderen über einen längeren Zeitraum stattfinden, der von klimatischen Variablen beeinflusst wird. In dieser Studie wurde die Vegetationsverschiebung in Bezug auf die Flächen, d. h. von Nadel- zu Laubwäldern (1579 km2) und umgekehrt (232 km2), in Bezug auf die Höhenverschiebung, d. h. 77 m höher für Laubwälder und 54 m niedriger für Nadelwälder, und in Bezug auf die Arten, d. h. von Laubwäldern zu Nadelwäldern und umgekehrt, im zukünftigen Klimawandelszenario festgestellt.

Das Ergebnis bestätigt, dass in den Wäldern in höheren Lagen ein höherer SOC-Vorrat vorhanden ist als in den Wäldern in niedrigeren Lagen. Es ist jedoch wahrscheinlich, dass die Menge an SOC abnimmt, während die Menge an AGTB in den zukünftigen Klimawandelszenarien zunimmt. Darüber hinaus zeigt das Ergebnis, dass die Vegetationsverschiebung von Nadel- zu Laubwäldern dominanter ist als von Laub- zu Nadelwäldern, und die Fläche der Laubwälder wird sich wahrscheinlich ausdehnen, während die Fläche der Nadelwälder in den zukünftigen Klimawandelszenarien wahrscheinlich schrumpfen wird.

Daher unterstreicht diese Studie die Notwendigkeit, die SOC-Menge zu erhalten und damit die Kohlenstoffemissionen aus dem Boden zu verringern. Sie unterstreicht auch die Bedeutung, die insbesondere Wälder in großen Höhen für die Bindung von atmosphärischem Kohlenstoff im Szenario des künftigen Klimawandels haben. Darüber hinaus unterstreicht die Studie, dass die Ausdehnung von Laubwäldern aufgrund von Vegetationsverschiebungen Vorteile für die Artenvielfalt, den SOC-Gehalt und die Widerstandsfähigkeit der Wälder mit sich bringen kann, aber auch Auswirkungen auf die von Nadelwäldern abhängigen Menschen und Unternehmen haben kann, da das Angebot an Waldprodukten geringer ist. Die Studie schlägt daher eine nachhaltige Bewirtschaftung von Hochwäldern vor, um das Klimaschutzpotenzial der Wälder zu erhöhen (Erhöhung der Kohlenstoffbindung und Verringerung der Kohlenstoffemissionen) und schlägt außerdem vor, Anpassungsmaßnahmen für gefährdete Gemeinschaften aufgrund des Klimawandels zu bewerten.

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Table of Contents

List of Figures

Acronyms

AGTB	Above-ground Tree Biomass
CMIP	Coupled Model Inter-comparison Project
DFRS	Department of Forest Research and Survey
FRA	Forest Resource Assessment
FRTC	Forest Research and Training Center
GHG	Greenhouse Gas
IPCC	Inter-governmental Panel on Climate Change
LRMP	Land Resource Mapping Project
MaxEnt	Maximum Entropy
MoFSC	Ministry of Forests and Soil Conservation
RFM	Random Forest Model
RMSE	Root Mean Square Error
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SSP	Shared Socio-economic Pathways
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United State Geological Survey

Part 1: Thematic context

1. Introduction

Nepal is known as one of the most vulnerable countries to climate change (GoN/MoFE, 2021). Impact of climate change has been seen in the forest ecosystem in terms of changes in species abundance, forest types, growth rate, structure of forests, tree mortality and tree vitality (Bhatta et al., 2021; Gebeyehu, 2019; Heidenreich & Seidel, 2022; Keane et al., 2020; Kelly & Goulden, 2008; Taccoen et al., 2022; Thapa & St. George, 2019; Trisurat et al., 2009). Furthermore, climate change impacts on the amount of soil organic carbon (SOC) (Kirschbaum, 2000; Zhao et al., 2021), above-ground tree biomass (AGTB) (Larjavaara et al., 2021; Li et al., 2022) and altitudinal shift of the vegetation (Li et al., 2020b; Parmesan & Yohe, 2003). Nepal selected as a test region due to its great difference in altitudinal thus climatic variability, can be considered as a chronosequence to study climate change impacts.

AGTB and SOC are important carbon pools in the terrestrial system (IPCC, 2006b). However, the amount of AGTB and SOC is influenced by topography (slope, aspect, altitude), climate (temperature and precipitation), species diversity and above-ground litter fall (Andivia et al., 2016; Gamfeldt et al., 2013; Rajput et al., 2017; Sun et al., 2019; Yan et al., 2015). Previous studies have shown that the future rising temperatures due to climate change most likely have an impact on AGTB and SOC (Azian et al., 2022; Larjavaara et al., 2021; Zhao et al., 2021). Increasing temperature contributes to a loss of soil organic carbon (Hartley et al., 2021) thus increase in soil carbon emission (Melillo et al., 2017) while contributing to an increase in the amount of AGTB (Day et al., 2008; Noguchi et al., 2022).

Several studies have demonstrated that the changes in the amount of AGTB and SOC also depend on the forest types (Baral et al., 2009; Pradhan et al., 2012). SOC is higher in broad-leaved forests than in coniferous forests (Chiti et al., 2012; Lee et al., 2020; Shapkota & Kafle, 2021; Sheikh et al., 2009). Similarly, AGTB is higher in a broadleaved forests than in coniferous forests (Ma et al., 2017; Yu et al., 2019). Thus, understanding the change in the amount of AGTB and SOC in the context of changing climate variables is crucial from the climate change and forest management perspectives.

Vegetation shifts from one forest type to another takes place over time (Hanewinkel et al., 2013) which increase species diversity and optimizes community structure (Ming et al., 2020). The vegetation shifts from coniferous forests to broadleaved forests shows various benefits in terms of conserving species diversity, and mitigating climate change impact by storing more soil organic carbon (Chiti et al., 2012; Lee et al., 2020; Shapkota & Kafle, 2021; Sheikh et al., 2009; C. Wu et al., 2017). Multiple studies also reported the impact of climate change on species composition (Feeley et al., 2011), the upward shift of the tree species (Li et al., 2020b; Parmesan & Yohe, 2003), and increasing/decreasing species richness (Adhikari et al., 2018; Zhou et al., 2013). The studies revealed that the changes in climate status bring several impacts on the forest ecosystem and evidently highlighted the possible impact of climate change on the vegetation shifts.

Moreover, changes in the climatic variables (temperature and precipitation) are reported to affect the shift in forest types (Chaitra et al., 2018; Sharma et al., 2017; Trindade et al., 2020). Coniferous forests are likely to occur in low rainfall areas while broadleaved forests are found in more humid locations (Bhatta et al., 2021). Therefore, the hypotheses can be made that increasing precipitation in the area of coniferous forests due to climate change may contribute to vegetation shift from coniferous to broad-leaved forests.

The prediction of SOC, AGTB and vegetation shifts is crucial to better understand the change in forest ecosystem. Both design-based and model-based estimators have been used for AGTB and SOC estimation (DFRS/FRA, 2014; Li et al., 2019; Malla et al., 2022). This study used a random forest model (RFM) for the estimation of SOC and AGTB. Currently, the random forest model has been widely used for estimating forest biomass and soil carbon (John et al., 2020; Lee et al., 2020; Li et al., 2020a; Nguyen & Kappas, 2020). Several studies found RFM superior to the regression model in terms of lowering mean squared error (Hounkpatin et al., 2018; Xie et al., 2021; Zhu et al., 2020), handling non-linear relations (Hengl et al., 2015; Pahlavan Rad et al., 2014), and indifference of assumptions of having probability distribution (normality) and no multicollinearity among independent variables (López-Serrano et al., 2016; Lu et al., 2016). For predicting the distribution of the species, the MaxEnt model has been widely used (Gajurel et al., 2014; Mahatara et al., 2021; Rai et al., 2022; Su et al., 2021). This study used the MaxEnt model to determine vegetation shifts of broad-leaved forests and coniferous forests.

Till now, several studies on SOC and AGTB have been carried out in the forest of Nepal. However, the studies on SOC, AGTB and species distribution have been done in small areas with shorter altitudinal gradients (Bajracharya et al., 2004; Baral et al., 2009; Gautam & Mandal, 2016; Ghimire et al., 2019; Pokhrel, 2018; Pradhan et al., 2012). These studies have been mostly confined to the estimation and potential current distribution of SOC and AGTB. Thus, studies on the change in the amount of SOC and AGTB at a larger scale due to future climate change scenarios are lacking. Similarly, studies on species distribution of flora and fauna have been confined to small areas in Nepal (Bista et al., 2018; Chhetri et al., 2018; Mahatara et al., 2021; Rai et al., 2022; Thapa et al., 2018). Most of the studies have been confined to faunal species distribution and to limited tree species distribution. Thus, studies on vegetation shifts (broad-leaved and coniferous forests) at a larger scale due to climate change in the future are lacking. The prediction of SOC, AGTB and vegetation shift from the perspective of the climate change scenario is a crucial task to mitigate and adapt to climate change impacts. A model to predict SOC, AGTB and vegetation shifts at the national level scenario based on the climatic variables has not been in place so far.

This thesis, therefore, focuses on understanding the predictor variables for soil organic carbon and above-ground tree biomass and assesses vegetation shifts in the future climate change scenarios. In particular, the thesis addresses the following research questions:

1. Do climatic variables affect the amount of SOC and AGTB?
2. Does future climate change contribute to an increase of SOC and AGTB stock in the forest ecosystem?

Does the future climate change contribute to vegetation shifts, i.e. spatial shift (area and altitude) and change in species composition?

To answer the above research questions, the most recent forest resource assessment (2010-2014) data from Nepal was used in this study. Moreover, climatic data (temperature and precipitation) from world climate data and topographical variables from FRA and from the United States Geological Survey (USGS) were used. Multiple regression, random forest model and MaxEnt model were applied to predict the target variables. The findings of this study provide plausible evidence and deeper insights into the forest dynamics for forest managers at all levels while formulating forestry sector plans and policies in the context of inevitable climate change in the future.

1.1 Soil organic carbon

Storing carbon in the forest soil is a means to mitigate climate change. Soil organic carbon (SOC) plays an important role in recycling the world's carbon (Shi et al., 2012; Song et al., 2012). It is one of the major carbon pools in the forest ecosystem (Gaucher et al., 2015; Neupane et al., 2018, FAO, 2020). The important source of organic carbon in the soil is dead organic matter that is incorporated into the soil by soil fauna through the organic matter transformation process (FAO, 2017). Soil organic carbon (SOC) stocks in the forest ecosystem are determined by several factors, such as climate, vegetation, topography (Yoo et al., 2006; Zhu et al., 2010), species diversity (Gamfeldt et al., 2013), litter fall (Andivia et al., 2016), and soil properties and soil moisture (Hounkpatin et al., 2018).

Previous studies have reported mixed results on the relationship between SOC and altitude. Several studies have shown a positive relationship between SOC and altitude (Badía et al., 2016; Dalmolin et al., 2006; Dieleman et al., 2013; Garten & Hanson, 2006; Sousa Neto et al., 2011; Zech et al., 2014) however, few studies have reported the opposite (Bangroo et al., 2017; Sheikh et al., 2009). Lower temperatures at higher altitudes slow down the decomposition of soil organic matter, leading to less carbon loss and an increase in SOC stock (Garten & Division, 2004; Liu & Nan, 2018).

Estimation of SOC in the forest is a crucial task in monitoring the forest ecosystem. Global Forest Resource Assessment (GFRA), 2020 has estimated 73.8 t/ha of SOC (FAO, 2020) while Forest Resource Assessment Nepal (at the national level) has estimated 66.8 t/ha of SOC (DFRS, 2015). Methods used for the estimation of SOC are design-based, model-based and machine-learning algorithms. All these methods have pros and cons one over another.

1.2 Above-ground tree biomass

Above-ground tree biomass (AGTB) includes the sum of stem biomass, branch biomass and foliage biomass (DFRS/FRA, 2014). AGTB shares major portion (81%) in the total biomass (Ekoungoulou et al., 2015) and therefore is a major source of biomass accumulation in the forest ecosystem. The GFRA has estimated 149.3 tons/ha of living biomass in the world (FAO, 2020). Similar to the SOC, the AGTB is also affected by multiple factors, for example, stand characteristics (tree age, density), topography (slope, aspect, altitude), and climate (temperature and precipitation) (Powell et al., 2010; Rajput et al., 2017; Shen et al., 2018; Van der Laan et al., 2014; Yan et al., 2015; Zhang et al., 2016)

The AGTB is the major variable for evaluating carbon sequestration potential and determining the total carbon stock of the forest ecosystem. The living biomass (above and below ground) of the world's forests contains 44% of the total terrestrial carbon (FAO, 2020). The conversion factor of 0.47, as recommended by the IPCC (IPCC, 2006a), was used to calculate above-ground carbon stock from AGTB which includes stem biomass, branch biomass and foliage biomass. A conventional design-based estimation (DFRS, 2015), model-based estimation (Li et al., 2019; Mohd Zaki et al., 2016; Pokhrel, 2018; Tian et al., 2014) and machine learning algorithm have been used to estimate the AGTB (Li et al., 2020a; López-Serrano et al., 2020; Nguyen & Kappas, 2020; Vorster et al., 2020) of the forests at local, national or global scale.

1.3 Distribution of forests

The forest cover of Nepal occupies 41.69% of the total area of the country. It has increased in the *Terai*, *Siwalik*, and Middle Mountain regions but decreased in the High Mountain and High *Himal* during the two decades from 2000 to 2019 (FRTC, 2022). The country is endowed with different forest types due to topographic and climatic variations. Forest types in Nepal have been classified by different people and organizations at different times. Stainton (1972) classified the forests of Nepal into 35 major types, with two sub-types for each of the Sal (*Shorea robusta*) forests and *Schima-Castonopsis* forests (Stainton, 1972). Similarly, Dobremez (1976) classified 77 vegetation types (Dobremez, 1976). Later, Jackson (1994) classified 24 vegetation types based on Stainton and Dobremez classification (Jackson, 1994). Moreover, the Tree Improvement Silviculture Component (TISC) of the Natural Resource Management Sector Assistance Program (NARMSAP) classified 36 vegetation types based on six main life zones with sub-zones (TISC, 2002). Forest resource assessment of Nepal during 2010-2014 identified 15 forest types in Nepal (DFRS/FRA, 2014; DFRS, 2015)as follows:

1. Terai Mixed Hardwood Forest : A mixed forest in the *Terai* region that none of the species has over 60% basal area
2. Upper Mixed Hardwood Forest: Mixed hardwood forest found >2000m
3. Lower Mixed Hardwood Forest: Mixed hardwood forest found in between 1000-2000m
4. *Shorea robusta* Forest: A forest which comprises *Shorea robusta* more than 60% basal area.
5. Chir Pine (*Pinus roxburghii*) Forest

6. *Quercus* Species Forest
7. Blue Pine (*Pinus wallichiana*) Forest
8. *Abies spectabilis* and *Abies pindrow* Forest
9. *Acacia catechu-Dalbergia sissoo* Forest
10. *Betula utilis* Forest
11. *Cedrus deodara* Forest
12. *Picea smithiana* Forest
13. *Cupressus torulosa* Forest
14. *Tsuga Dumosa* Forest
15. *Juglans wallichiana* Forest

More forest types in the study area indicates larger variations. Thus, forest resource assessment used a large number of sample plots to represent all the forest types in the assessment for the better estimates of the targeted variables.

1.4 Vegetation shifts

Vegetation dynamics in relation to climate provide a comprehensive understanding of the forest ecosystem. Climate acts as an important driver of vegetation patterns affecting the growth, migration and existence of the tree species (IPCC, 1996). The upward shift of the vegetation has been observed by several studies due to climate change (Gaire et al., 2014; Li et al., 2020b; Parmesan & Yohe, 2003). Vegetation shift in relation to climate change has been mentioned in terms of forest type change (Chaitra et al., 2018), and the spatial distribution of the forests (Hanawalt et al., 2018; Hufnagel & Garamvölgyi, 2014b). One forest type is replaced by another forest type after a long period of time due to natural processes or human disturbances. Similar vegetation shifts (i.e. forest type change and habitat expansion/shrinkage of the forests) are expected to occur in the future climate change scenarios.

1.5 Climates and climate change impact

The mean annual temperature of Nepal ranges from -12^0C to 26^0C while the mean annual precipitation ranges from 200 mm to 5000 mm (Karki et al., 2016). Warming in Nepal has been observed based on historical observational data. The mean annual temperature is expected to increase by 0.002^0C/year at the minimum and by 0.056^0C/year the maximum, with the highest rate of increase in the higher altitudes., The amount of precipitation in the future is also likely to increase by 2%-6% between 2016-2045 period and by 8%-12% during 2036-2065 (GoN/MoFE, 2021). Similarly, Darjee et al., reported the rate of increase in temperature in Mountain, Middle hills and lowland regions by 0.0618^0, 0.0638^0, and 0.0178^0Cyr^{-1}, respectively between 1988-2018 period (Darjee et al., 2022).

Climate change impacts have been seen in many areas, including forests and biodiversity (ADB & WB, 2021). Climate change causes both positive and negative impacts on the forests. The positive impacts include an increase in species richness (Zhou et al., 2013), growth of conifer forests (Wu et al., 2019), and an increase in wood production and carbon stock (Eggers et al., 2008). While negative impacts include the depletion of the highland ecosystem (Manish et al., 2016), habitat shrinkage of medicinal and aromatic plants (MAPs) (Shrestha et al., 2022), threatened conifers (Xie et al., 2022), and increased infestation of pest and invasive species (Gebeyehu, 2019). Thus, climate change is causing significant impacts on the forest ecosystem, and it plays a crucial role in shaping the dynamics of forest ecosystems.

1.6 Structure of the comprehensive summary

The first part of this comprehensive summary provides an overview of the thematic context, highlighting the introduction, research questions, conceptual framework, and methodological approach. It also provides information needed to understand climate change impact on soil organic carbon, above-ground tree biomass, and vegetation shift. The thesis presents the climatic variables as a determinant of the SOC, AGTB, and vegetation shift. Firstly, the study found that the climate influences the amount of SOC, as there is an inverse relationship between temperature and altitude. Secondly, the study found that the amount of AGTB increases with the increase in temperature as temperature helps the growth of the trees. Lastly, the study found that the changes in the amount of temperature and precipitation influence the distribution of the forest species. The changes in forest types was found to vary with the changes in altitude and climate.

In the second part of this comprehensive summary, the published articles, as a part of this thesis, have been summarized and discussed. The articles are as follows:

> Malla, R., Neupane, P.R and Köhl, M. 2022. Modeling soil organic carbon as a function of topographic and stand variables. *Forests*, 13:1391
> https://doi.org/10.3390/ f13091391

Malla, R., Neupane, P.R and Köhl, M. 2023. Assessment of above ground biomass and soil organic carbon in the forests of Nepal under projected scenario. *Frontiers in Forests and Global Change*, Vol 6:1209232.
https://doi.org/10.3389/ffgc.2023.1209232

Malla, R., Neupane, P.R and Köhl, M. 2023. Climate change impacts: vegetation shift of broad-leaved and coniferous forest.
Trees, Forests and People, Vol 14:100457
https://doi.org/10.1016/j.tfp.2023.100457

Finally, the thesis concludes the study based on three published papers under conclusions of the cumulative dissertation followed by an outlook for future considerations based on the findings of this study.

2. A Conceptual Framework of climate change impact

Greenhouse gas (GHG) emission leads to global warming resulting in climate change. Climate change is a change in the state of the climate identified by changes in the mean and/or the variability of its properties that persists for decades longer (IPCC, 2014). The global average temperature has increased by 1.1^0C from the period 1850-1900 to 2011-2020 (IPCC, 2023). An increase of global warming per decade in all the continents has been reported to rise by 0.13^0C during the past 50 years from the period 1948-1998 (Pepin & Seidel, 2005). Further, the rate is supposed to increase by 0.25–0.48 °C/decade until 2085 (Nogués-Bravo et al., 2007). Impacts of climate change have been observed in tree-line shift (Devi et al., 2020), tree species distribution (Thapa et al., 2013), forest biomass (Poudel et al., 2011), tree growth (Zhu, 2020), distribution of medicinal and aromatic plants (Rana et al., 2020), invasive alien plant species (Shrestha et al., 2018), and soil organic carbon (Zhao et al., 2021). Although the climate change impacts have been seen in several aspects of a forest ecosystem, this study confines the impacts of climate change on AGTB, SOC and vegetation shifts.

AGTB and SOC are crucial components of the forests in the context of climate change. They are the functions of several variables, such as slope, aspect, altitude, vegetation, soil moisture, species diversity, temperature, and precipitation (Fissore et al., 2008; Larjavaara et al., 2021; Li et al., 2022; Yoo et al., 2006; Zhu et al., 2010). Changes in the SOC and AGTB are the results of changes in climatic variables (Hanawalt & Whittaker, 1976). Topographic variables (altitude, slope and aspects) do not directly affect AGTB and SOC. However, these variables (particularly altitude) can be used as proxy variables for the estimation of the SOC and AGTB.

The formation of SOC mainly depends on the rate of decomposition of organic matter that is influenced by temperature (Zinn et al., 2018). Besides temperature, the precipitation influences soil moisture and hydrological processes (Heisler & Weltzin, 2006) which matters in SOC cycling (Aanderud et al., 2010). Similarly, the formation of AGTB also depends on the warming temperatures that enhances tree growth (Way & Oren, 2010). Temperature and precipitation directly affect stand structure, resulting in a change in AGTB (Ma et al., 2023).

Moreover, previous studies show the impact of climate change on the tree species composition/distribution (Chhetri et al., 2018; Trisurat et al., 2009; Wang et al., 2017). These studies support the potential impact of climate change on vegetation shift, for example, coniferous forest into broad-leaved forests or vice versa. Broad-leaved forests and coniferous forests are found in different climatic conditions in Nepal, mainly characterized by high rainfall area and low rainfall areas respectively (Bhatta et al., 2021). A change in existing climatic conditions in the future scenario is supposed to influence the distribution of broad-leaved and coniferous forests. Change in the variables, such as AGTB, SOC, and vegetation shift due to climate change, is thus likely to affect species composition, structure and growth of the forests.

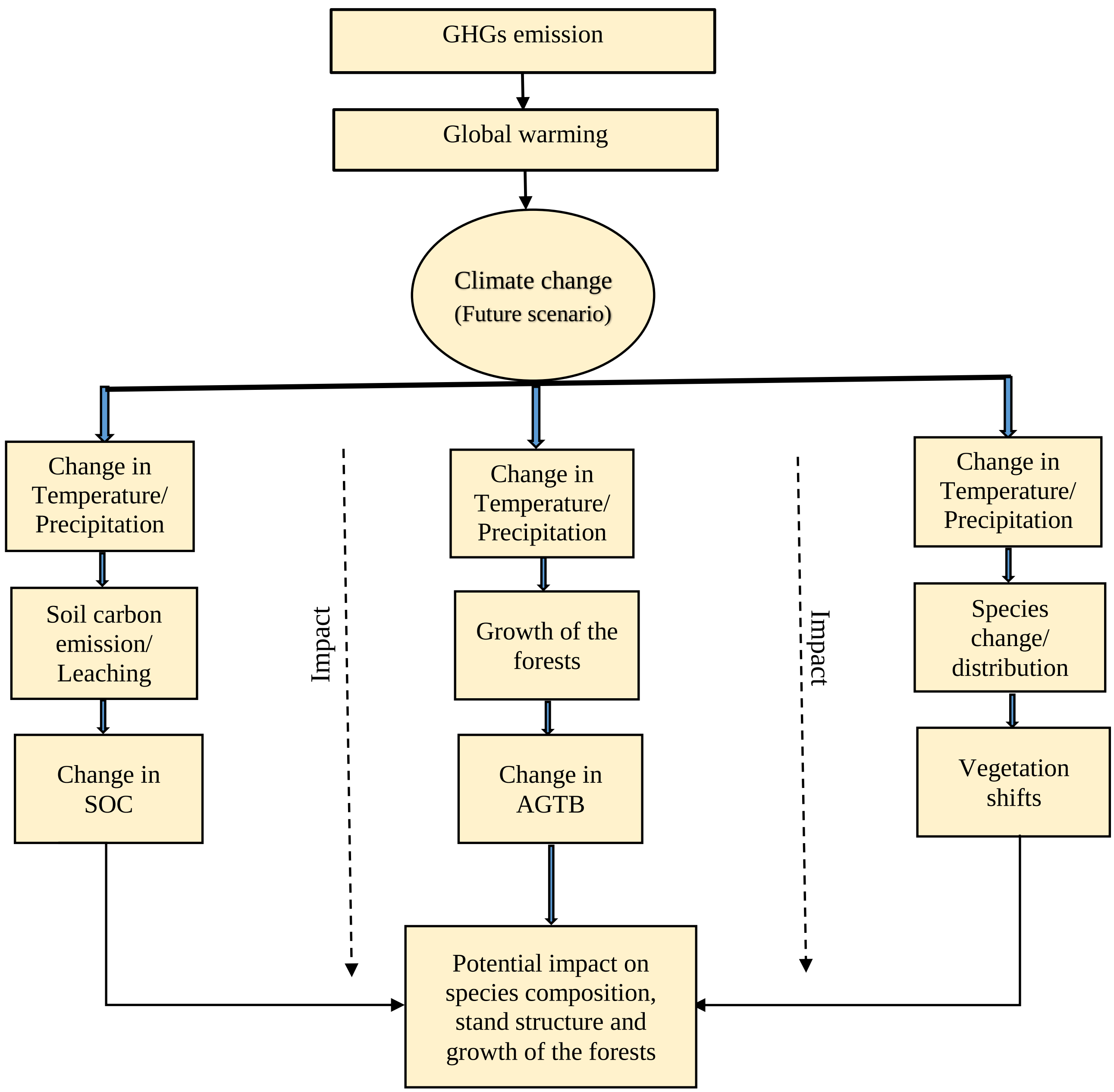

Figure 1: Conceptual framework of climate change impact on SOC, AGTB and vegetation shifts

The thesis uses a conceptual framework to show the connections between greenhouse gas emissions, global warming, climate change, forest variables, and potential impacts (Figure 1). Following the framework, this thesis particularly investigates the impact of climate change on SOC, AGTB, and vegetation shifts.

Part II: Integration of the articles into the thematic context

Part II briefly describes the core research papers followed by a detailed description of the individual papers in the context of this thesis. A detailed description of the methods and results is given in the respective papers.

1. Malla et al., (2022): Modeling soil organic carbon as a function of topographic and stand variables

The paper[1] was written by Rajesh Malla, Prem Raj Neupane and Michael Köhl. It was published in the peer reviewed international journal 'Forests' in 2022.

1.1 Summary of the paper (Malla et al., 2022)

Soil organic carbon (SOC) is one of the major carbon pools in the terrestrial ecosystem that serves in global carbon cycling. The SOC is influenced by several factors, such as topography, forest type, and forest disturbance, along with changes in the climatic variables. Due to diverse climatic and altitudinal variations, Nepal was chosen as the study area. To investigate the potential predictor variables for the estimation of SOC, a multiple regression model was used with six different predictor variables (topographic variables i.e. altitude, slope, and aspect and forest variables i.e. basal area crown cover, and above-ground tree biomass) as recorded in the third national-level forest resource assessment (2010-2014) of Nepal. Altogether, data from 862 permanent sample plots were used for model development (80%) and model validation (20%). A significant correlation between the SOC stock and altitude (r = 0.76) followed by crown cover and slope was found in the study. Altitude alone explained 58% of the variability of the SOC stock and showed an increasing rate of change in SOC with the increase in altitude. Thus, altitude was identified as a suitable predictor of SOC stock for extensive areas with high altitudinal variation followed by crown cover and slope. A positive correlation between SOC stock and altitude showed the significance of high-altitude forests from the perspective of climate change mitigation. Altitude, a proxy of temperature, is likely to provide insights into the influence of changing temperature patterns on SOC due to future climate change. It is recommended to conduct further studies on

[1] **Authors Contribution:** R.M. developed the study design, P.R.N. and M.K. commented on the draft design. R.M. was responsible for data acquisition, carried out the data analysis, and drafted the manuscript. P.R.N. and M.K. commented the draft and contributed on drafting to the final stage of the manuscripts. All authors have read and agreed to the published version of the manuscript.

different forest types and SOC along the altitudinal gradient in Nepal to deal with the climate change related problems.

1.2 Discussion of the first paper in the thematic context

This paper provides insights into the relation between SOC (as a response variable) and other variables (predictors). The paper shows a significant effect of the predictor variables on the response variable in the model developed. This study addresses the following research questions:

1. Do topographic variables (slope, aspect, altitude) influence SOC significantly?
2. Do forest variables (crown cover, basal area, AGTB) influence SOC significantly?
3. Which predictor variable/s is/are appropriate to use in the estimation of SOC?

The amount of SOC is influenced by various factors such as climatic, edaphic, and biotic factors (Schimel et al., 1994), and topographic factors (Patton et al., 2019; Zhu et al., 2019). Particularly, topographical factors are the main factors contributing to spatial variability of SOC (Chen et al., 2016; Lozano-García et al., 2016; Yimer et al., 2006), and induce heterogeneity in SOC resulting in large uncertainties in SOC storage (Hancock et al., 2010; Zhu et al., 2017). Among the topographical variables, our study showed altitude as the strongest predictor of SOC followed by slope, while aspect was found to be statistically insignificant. Altitude was shown to have a strong positive relation with SOC. Findings of this study are supported by several other studies under various altitudinal ranges such as Meghalaya, India (150-1961m); Brazilian Atlantic Forest (100-1000m); Mt. Kilimanjaro, Tanzania (750-4000m); Southern Appalachian, USA (235-1670m); Saruwaged Mountain, Papua New Guinea's (100-3050m); Moncayo Massif, SW Europe (1000-1600m); Mt Changbai, China (700-2000m); Tropical Montane Forest (1000-3600m); Bale Mountains, Ethiopia (2390- 3250m); Spain (607-1168m) and Ethiopia (2034m-2410m) (Badía et al., 2016; Chaturvedi & Sun, 2018; Dalmolin et al., 2006; Dieleman et al., 2013; Garten & Hanson, 2006; Gebeyehu et al., 2019; Parras-Alcántara et al., 2015; Schindlbacher et al., 2010; Sousa Neto et al., 2011; Tashi et al., 2016; Zech et al., 2014).

Altitude and temperature in Nepal are negatively correlated (Jha, 1992). Since altitude and SOC show strong positive correlation in this study, it implies a negative correlation of temperature with SOC. The concentration of SOC stock per hectare increases with an increase in altitude (lower region to high mountain region). This is due to a decrease in temperature at the higher altitude resulting lower rate of SOM decomposition by the microbes (Deng et al., 2014; Garten, 2006).

Consequently, lower temperature at a higher altitude is likely to control the retention of SOC (Zhang et al., 2021; Zinn et al., 2018) which shows that a decreasing trend of temperature from lower to higher regions is contributing to a higher rate of SOC accumulation.

Furthermore, the extraction of forest products (litter, branches, timber) from the forest can also influence the accumulation of SOC due to the reduced availability of forest organic material that can be converted to soil organic matter (Baral & Katzensteiner, 2015). Forest product extraction depends on the accessibility of the forest. Only 51.5% of the forest is accessible (located at slope $<45^0$) in Nepal (DFRS, 1999). Accessing forests at higher altitudes is difficult due to the rugged terrain compared to lower regions. It is supported by the results that forest disturbances by humans (tree cutting, bush cutting, litter collection, lopping and cattle grazing) are lower at higher altitudes (DFRS, 2015). Therefore, it can be concluded that the distribution of SOC is likely to be concentrated more in the region with fewer anthropogenic disturbances compared to a region of higher disturbance (Wilcox, 2010).

In Contrast, some studies have also shown decreasing stocks of SOC with increasing altitude (Bangroo et al., 2017; Sheikh et al., 2009) and no significant relation between SOC and altitude (Devi, 2021). These studies were conducted within shorter altitudinal ranges i.e. 500-1200m, 1600-2200m, 1800-2200m, and 2200-2500m. Due to the underlying short ranges of altitudes, other variables may have more effect on SOC. A study on SOC in the Mawer Range in India for two attitudinal zones (1800 – 2200m and 2200 -2500 m) shows that mean values of SOC decreases with increasing altitude. However, the differences presented are not statistically significant at the 95% confidence intervals (Sheikh et al., 2009).

Previous studies found that the forest soil organic carbon stocks increase with altitude due to slow soil organic matter decomposition at the colder higher elevation sites (Schindlbacher et al., 2010; Tashi et al., 2016). This finding corroborates with the result of our study.

The model of the study which used altitude as the sole predictor of SOC produced two-thirds of the accuracy of the model which can be an option to assess SOC distribution at the national scale. In addition, the present model gives an avenue to use other predictor variables (along with altitude) such as bioclimatic variables and human disturbances to build more robust models for the estimation of SOC in the future. The phenomena of decreasing temperature with increasing altitude suggest that altitude may be considered as a proxy for temperatures in the studies examining the influence of future climate change on SOC stock. Our study provides a basis for studying the effect of changing temperature patterns due to climate change on the SOC stock.

Globally, soil alone contains more carbon than atmosphere and vegetation combined (Montanarella Luca et al., 2015). Thus even a small variation in SOC concentrations can significantly affect the global carbon cycle (Walter et al., 2016). Higher altitude forests have the highest biomass density and also store a large amount of SOC in Nepal (DFRS, 2015). According to our result, an increasing rate of change in the amount of SOC with an increase in altitude shows that higher altitude forests are of paramount importance from a climate change mitigation perspective. They have been contributing to climate change mitigation by acting as a carbon sink both in trees and forest soil.

2. Malla et al., (2023): "Assessment of above ground biomass and soil organic carbon in the forests of Nepal under climate change scenario"

The second paper has been prepared as a part of this thesis. The paper[2] was written by Rajesh Malla, Prem Raj Neupane and Michael Köhl. It is published in a peer reviewed international journal 'Frontiers in Forests and Global Change' in 2023.

2.1 Summary of the paper (Malla et al., 2023)

Climate, topography, vegetation and forest management practices are the factors that influence the amount of soil organic carbon (SOC) and above-ground tree biomass (AGTB) of the forests. This study focused on assessing the relationship between various predictor variables (topography, forest and bioclimatic variables) and response variables (SOC and AGTB) from the perspective of climate change scenarios. The study was conducted throughout Nepal using nationwide forest resource assessment data (2010–2014). In order to understand the relationship of the SOC and AGTB with the predictor variables, we used a Random Forest Model (RFM) under future climate change scenarios. Altogether 19 bioclimatic variables accompanied by other variables such as altitude, aspect, basal area, crown cover development status, distance to settlement forest types, number of trees, macro-topography, management regime, physiographic zones, slope, and soil depth were included in the study as predictor variables. The study used 737 (70%) samples as training data for model development and 312 (30%) samples were used as testing data for model validation. RMSE, RMSE% and adjusted R^2 of the Random Forest Model for SOC estimation were found to be 9.53 ton/ha, 15% and 0.746 respectively while the same statistics for AGTB were found to be 37.55 ton/ha, 21.74% and 0.743 respectively. Among the predictor variables, changes in temperature and precipitation showed stronger effect on the amount of SOC and AGTB in the projected scenario i.e. CMIP6, SSP2 4.5 for 2040-2060. We found that the amount of SOC decreased by 3.85%, while AGTB increased by 2.96% in the projected scenario. The proposed approach can be a better option for understanding the changes in the amount of SOC and AGTB in the future scenarios.

[2] **Authors Contributions:** R.M. developed the study design, P.R.N. and M.K. commented on the draft design. R.M. was responsible for data acquisition, carried out the data analysis, and drafted the manuscript. P.R.N. and M.K. commented the draft and contributed on drafting to the final stage of the manuscripts. All authors have read and agreed to the published version of the manuscript.

2.2 Discussion of the second paper in the thematic context

This paper focuses on assessing the impact of climate change on the amount of SOC and AGTB in the future scenario, 2040-2060. The findings show a positive impact of climate change on the amount of AGTB, and a negative impact on the amount of SOC. This study addressed the following research questions:

1) Which variables (topographic, forest variables and climatic variables) are significant in influencing the amounts of AGTB and SOC?

2) Are these variables likely to contribute to the amount of AGTB and SOC under the future climate change scenario?

According to previous studies, climate change i.e. rising temperatures in particular in the future likely has a negative effect on the amount of AGTB (Larjavaara et al., 2021; Li et al., 2022) and SOC (Kirschbaum, 2000; Zhao et al., 2021). There are also studies showing a positive effect of rising temperature on the amount of AGTB and SOC under different climate change scenarios (Azian et al., 2022; Fu et al., 2017). But, this study predicted an upward trend in the amount of SOC, while a downward trend in the amount of AGTB in the future climate change scenario. The study showed a mean temperature of the wettest quarter (Bio8) as a major predictor variable to estimate the amount of SOC in particular. In general, climatic variables dominated other variables in predicting the amount of SOC. Similar to our study, previous studies have reported the effects of climate (temperature and precipitation) on SOC (Alani et al., 2017; Chen et al., 2015; Fang et al., 2022; Odebiri et al., 2020; Sun et al., 2019). However, other studies also found altitude as a major variable for SOC prediction (Dieleman et al., 2013; Odebiri et al., 2020). This is also true because altitude does not directly influence SOC but is an indicator of various climatic functions that govern different vegetation and soil formation processes (Hanawalt & Whittaker, 1976). Thus, altitude can be used as a proxy for climatic variables (Malla et al., 2022). Owing to global warming, surface temperature will continue to increase, at least, until 2050 under all emission scenarios (IPCC, 2021). The result shows an increase in temperature (in the future scenario) leads to a decrease in the amount of SOC, which is supported by other studies (Liu et al., 2021; Zhao et al., 2021). Similarly, the negative association of precipitation (in the future scenario) with the amount of SOC in our result is similar to the result reported by (Alani et al., 2017).

On the other hand, our study reported the effect of climate attributes on AGTB, particularly of the maximum temperature of the warmest month (Bio5) and precipitation of the driest month (Bio14) which is supported by other studies (Bennett et al., 2020; Larjavaara et al., 2021; Wang et al., 2017). The RFM of this study shows an increase of AGTB under future climate change scenarios is consistent with the results reported by (Day et al., 2008; Saeed et al., 2019; Wang et al., 2019). An increase in precipitation in the driest months (Bio14) helps increase AGTB by lengthening the growing season that supports plant growth (Vaganov et al., 1999). The study results show a positive effect of Bio14 and warmer in the summer (similar to Bio5) with AGTB is consistent with the study conducted by (Devi et al., 2020; Lewis et al., 2013; Noguchi et al., 2022). Unlike the forests in Nepal, rising temperature is likely to decrease above-ground biomass in the old-growth tropical forests (Larjavaara et al., 2021) which could be due to slow growth at the old age.

Thus, we conclude that the climatic variables (temperature and precipitation) influence the amount of SOC and AGTB in the future climate change scenario. However, the effect of climate on the SOC and AGTB is opposite (positive with AGTB while negative with SOC). Combining bioclimatic variables with other variables in the machine learning model, i.e. RFM for the prediction of SOC and AGTB can be a viable option to better understand the forest ecosystem from the perspective of climate change scenario.

3 Malla et al., (2023): "Climate change impacts: vegetation shift of broad-leaved and coniferous forests"

The third paper was prepared as a part of this thesis. The paper[3] was written by Rajesh Malla, Prem Raj Neupane and Michael Köhl. It is published in the peer reviewed international journal 'Trees, Forests and People' in 2023.

3.1 Summary of the paper (Malla et al., 2023)

The impact of climate change has been observed in several components of forest ecosystems, such as forest structure (e.g., species distribution, habitat composition), forest composition (e.g., species composition) and forest processes. In this study, we intended to answer how future climate change is likely to cause an impact on vegetation shift i.e. spatial shift (area and altitude) and species composition of broad-leaved and coniferous forest. The study was carried out throughout Nepal representing lower to higher altitudinal regions. Altogether 392 presence points (observations) for broad-leaved forests and 99 for coniferous forests were used in the study. These occurrence points, accompanied by bioclimatic variables (temperature and precipitations) and topographical variables (Elevation, Slope and Aspect), were used as input data in a Maximum Entropy (MaxEnt) model to predict the potential distribution of the coniferous forests and broad-leaved forests at present and their shift in terms of area, altitude and species composition in the future scenario.

Our results showed that the potential areas of the near current (1970-2000) coniferous forests are likely to be shifted into broad-leaved forests under a climate change scenario (SSP2 4.5 for 2050) and vice versa. The total vegetation shift area of Nepal was found to be approximately 1800 km^2 (i.e. over 3% of the total forest area). Out of the total vegetation shift area, almost 90% percent of the coniferous forest was supposed to be replaced by the broad-leaved forests, while a small portion of the broad-leaved forest was replaced by the coniferous forest. The vegetation shift from the coniferous forests to the broad-leaved forest is more dominant than the reverse under the climate change scenario. Similarly, the result shows that the distribution of coniferous forests was found

[3] **Authors Contributions:** R.M. developed the study design, P.R.N. and M.K. commented on the draft design. R.M. was responsible for data acquisition, carried out the data analysis, and drafted the manuscript. P.R.N. and M.K. commented the draft and contributed on drafting to the final stage of the manuscripts. All authors have read and agreed to the published version of the manuscript.

54 m downward shift at higher altitudes (i.e. 4928m to 4874m) whereas 214m upward shift at lower altitudes (i.e. 796m to 1010m) in the future climate change scenario. In the case of the broad-leaved forest, the result shows that the distribution of broad-leaved forests was found to shift 77m upwards in higher altitudes (i.e. 3767m to 3844m altitude) while no downward shift at lower altitudes in the future climate change scenario. The altitudinal variation of the coniferous forest seems to be shrinking while it is expanding for broad-leaved forests in future climate change.

3.2 Discussion of the third paper in the thematic context

The third paper focuses on assessing the impacts of climate change on vegetation shifts. The overarching objective of this study was to explore how broad-leaved forests and coniferous forests will respond to climate change in future climate change scenarios. The broad-leaved forests and coniferous forests are different in terms of their impacts on social, ecological and economic aspects. The broad-leaved forests benefit more than the coniferous forest in providing forest ecosystem services such as species diversity, hot temperature mitigation, soil organic carbon and water yield (Chiti et al., 2012; Joshi et al., 2022; Komatsu et al., 2008; Lindbladh et al., 2022; Schwaab et al., 2020). Nowadays, the demand for broad-leaved forests is increasing in the coniferous species-dominated area, particularly in the middle hills of Nepal. It is believed that broad-leaved forest provides multiple benefits than coniferous forests. The paper shows that the vegetation shift from coniferous forests to broad-leaved forests in the future climate change scenario is more dominant compared to the broad-leaved forests to coniferous forests. Previous studies also reported the impact of climate change on species composition (Feeley et al., 2011) and increasing/decreasing species richness (Adhikari et al., 2018; Zhou et al., 2013). The findings of the study support the hypothesis of climate change impact on vegetation shifts, i.e. one tree species to another species. Moreover, the potential shrinkage of the habitat of the coniferous forests in the higher altitudes in our study is similar to the findings reported by (Fyllas et al., 2022). It reports that the tree species at higher elevation is experiencing more pronounced potential habitat shrinkage.

Similarly, the findings of this paper show both upward and downward shifts for coniferous species while only upward shift for broad-leaved species. In the case of coniferous species, the upward shifts are likely to take place at the lower altitudinal regions while upward shifts are likely to occur at the higher altitudinal regions for the broad-leaved species. As a result, the altitudinal range of the coniferous forests is narrowing down and is expanding for broad-leaved forest. Climate change impact of the upward shifts of tree species were reported by various studies (Li et al., 2020b; Parmesan & Yohe, 2003).

The distribution of the broad-leaved forest and the coniferous forest is largely determined by annual precipitation (Bio12) and elevation. In the mountain areas of Nepal, coniferous forests are confined to the low precipitation area compared to broad-leaved forests (Bhatta et al., 2021) which shows that low precipitation favors coniferous forests compared to the broad-leaved forests. In the future climate change scenario (SSP2 4.5 scenario for 2050), the amount of precipitation increases which could lead to increased spatial distribution of the broad-leaved forest. However, elevation does not directly affect the distribution of the species, it is a proxy for climatic functions (Hanawalt & Whittaker, 1976) due to an inverse relationship between elevation and temperature in Nepal.

Similarly, the temperature increase in future climate change is supposed to favour the expansion of broad-leaved forests. The lower regions of Nepal (Terai, Siwalik and Middle Mountain with higher temperatures) are covered mostly with broad-leaved forests. Particularly, the increase in temperature is more pronounced in higher altitudes of Nepal (GoN/MoFE, 2021) which supports our findings in the future scenarios, i.e. the upward shift of broad-leaved forests. The impact of climate change is not only limited to the area of forest change but is also seen in the altitudinal shift of the newly formed forests. As a result of forest change, it could affect the accumulation of soil organic carbon (SOC), species diversity, and climate resilient capacity of the forests in future climate change scenarios. These findings support studies indicating that the broad-leaved forests reveal an increase in the resilience capacity of the forest against climate change because of having higher species diversity (Joshi et al., 2022) and a higher amount of SOC stock (Elith et al., 2006; Grimmett et al., 2020). Increasing the area of broad-leaved forests in the future climate change scenarios will have positive effects on the forest ecosystem in terms of carbon sequestration, species diversity and resiliency of the forests.

Moreover, human disturbance (i.e., tree harvest) also contributes to future species distribution along with climate change (Wang et al., 2019). Cutting pine trees in the pine- dominated areas in favor of obtaining broad-leaved trees has been practiced in Nepal to fulfill multiple demands of the people. Tree harvesting is conducted in Nepal according to the forest operational/management plan of the community forests (Baral & Vacik, 2018). Climate induced severe events such as forest fires (Hill & Field, 2021), forest pests/diseases (Boyd et al., 2013), invasive alien plant species (Bhatta et al., 2020) cause impact on tree species diversity. These human intervention and climate-induced severe events coupled with climate change may pose a combined effect on the vegetation shifts. Further studies on vegetation shift need to include human disturbances and climate-induced severe events into the species distribution model for better prediction.

Part III: Conclusions of the cumulative dissertation

This PhD study used a large area (national-level) dataset from the forest resource assessment of Nepal (2010-2014). This is the first assessment carried out in Nepal using robust forest inventory methodology and recorded soil samples to analyze soil organic carbon. Using a large area dataset for the study of climate change impact on the forest variables supports a better prediction of climate change in the future. The application of widely used models such as multiple regressions, random forest model and MaxEnt model to better estimate the target variables has enriched the results of the study. A chronosequence study to climate change impact carried out in a country like Nepal with large altitudinal thus climatic variations using national-level dataset helps to understand the interactions between climatic variables and forest variables more deeply. The findings of this study can be a basis for hypothesis/theory development in the future for similar other studies.

1. Altitude as a proxy variable for the prediction of soil organic carbon

Several variables (forest, topography, climate) are responsible to affect soil organic carbon at different extents. Among all, which variable affects more significantly to the soil organic carbon stock was an important research question in the study. The multiple regression model used in the study helped to determine significant predictor variables for the prediction of soil organic carbon. Altitude is considered the most significant predictor variable in the model to predict soil organic carbon.

Several studies reported the relationship between temperature and soil organic carbon. The temperature of the soil is a determining factor for microbial activities which regulates soil organic carbon stock. Warmer temperature supports organic matter decomposition through microbial activities resulting in a lower amount of soil organic carbon (Garten & Division, 2004). Conversely, cooler temperature slows down microbial activities thus helping to retain soil organic carbon. The temperature decreases with the increase in the altitudinal gradient in Nepal (Jha, 1992). An increase in soil organic carbon stock is seen from the lower to the higher region. The altitude itself does not affect soil organic carbon but the altitudinal-induced variation in the climate is responsible.

The higher rate of soil organic accumulation in the higher altitudinal regions compared to the lower altitudinal regions is an interesting result of this study. This result provides more insight into the dynamics of SOC. It clearly depicts that the higher altitudinal forest of Nepal contributes to a higher amount of carbon sequestration in the form of soil organic carbon as compared to lower regions. This relation highlights the need for sustainable management of high-altitude forests to maximize the mitigation potential of the forest ecosystems protecting fragile landscapes in Nepal. The result of this study supports generalizing the positive relation between altitude and SOC. The future study on different forest types and SOC in Nepal on a larger scale could provide a better understanding of forests' contribution to climate change mitigation and possible solutions to deal with the climate change problem.

2. Projected climate change impact on soil organic carbon and above-ground tree biomass

Soil organic carbon and above-ground tree biomass play an important role in climate change mitigation by sequestering atmospheric carbon into forest ecosystems. Carbon emissions from different sources increase the rate of global warming. Thus, projected climate change shows an increase in temperature and precipitation. The study intended to provide evidence on how projected climate change impacts the soil organic carbon and abover-ground tree biomass. Applying the random forest model helped to analyze the impact of climate change in soil organic carbon and above-ground tree biomass

The result of the study confirms the effect of climatic variables (temperature and precipitation) on the amount of soil organic carbon and above-ground tree biomass in the future climate change scenario. However, the effect of climate on the soil organic carbon and above-ground tree biomass is opposite (positive with above-ground tree biomass while negative with soil organic carbon). Increasing amounts of soil organic carbon and above-ground tree biomass are important indicators of atmospheric carbon sequestration for mitigating climate change impact.

The increasing trend of above-ground tree biomass in the future climate change scenario shows its potential contribution to climate change mitigation. Moreover, an increase in forest biomass will increase the available amount of harvesting wood products (HWPs). The increase in the amount of HWPs could contribute to climate change mitigation efforts by replacing and therefore decreasing the demand for emission intensive products such as steel or cement. Conversely, the decreasing trend of soil organic carbon stock in the future climate change scenario can be a serious issue from different perspectives such as climate change mitigation, soil health, etc. Thus, maintaining soil organic carbon under future climate change is a crucial task which should be addressed relatively soon.

This study proposed an approach for estimating the soil organic carbon and above-ground tree biomass of Nepal using forest inventory data combined with bioclimatic variables can be a better option to predict the trend of soil organic carbon and above-ground tree biomass under projected climatic variables. Further studies on maintaining forest soil organic carbon under rising temperatures by management activities are needed. For example, maintenance of crown cover helps in lowering the soil temperature which might be a possible intervention to be considered to retain soil organic carbon in the future.

3. Climate change impact on vegetation shifts (broad-leaved forest and coniferous forest) in terms of area, altitude and species change.

Several studies have reported that climate change as a driver of the spatial distribution of tree species. The upward shift of Himalayan tree species has been observed in Nepal in correlation with increasing temperature (Gaire et al., 2014). Climate change impact is not limited to upward shift, rather change in species composition, habitat suitability, forest fire events and increasing pests/pathogens and invasive alien species have been observed as well. This study intended to assess how broad-leaved and coniferous forests would respond to future climate change scenarios. A very popular species distribution model (MaxEnt model) applied in the study assisted in assessing vegetation shift against projected climatic variables.

The result of this study revealed the impact of climate change on the vegetation shifts of coniferous forests and broad-leaved forests. However, the impact of climate change has been seen in both forests, the vegetation shifts from coniferous to broad-leaved forest is more dominant than vice versa. The total area of broad-leaved forest is likely to expand in the future while coniferous forest is likely to lose its total area. The impact of climate change is not only limited to the area of forest change but is also seen in the altitudinal shift of the newly formed forests.

Vegetation shifts to broad-leaved forests under climate change scenario could benefit in terms of increasing species diversity, amount of soil organic carbon stock and climate resilient capacity of the forest. However, this vegetation shift may negatively affect the coniferous forest-dependent local people and forest-based enterprises by losing the benefits from these forests in the future.

Adaptation measures for vulnerable communities need to be assessed to overcome climate change impacts in the future.

Broad-leaved forests are generally seen to be more beneficial than coniferous forests due to their capacity to provide multiple benefits to the people. However, for the coniferous forest-dependent people and forest-based enterprise, an intervention is needed to maintain coniferous forests against climate change. Further studies on vulnerability of the coniferous forest-dependent people and forest-based enterprise and adaptation measures is seen as a potential area of research.

4. Outlook

Forests play is a significant role in climate change mitigation through various ways i.e. by sequestering atmospheric carbon in the form of biomass and by availing harvested wood products (means of energy and material substitution). Climate-smart forestry has been a popular approach to increase climate benefits from the forests and forestry sector from the perspective of climate change impact. It focuses on reducing green house gas emission, making forest climate resilient and increasing forest based benefits through sustainable management of the forest.

The impact of climate change has been seen in several areas, including forest ecosystems. The change in species composition, stand structure, biomass, soil carbon, soil moisture, and biodiversity have been reported by the studies as the result of climate change. Climate change mitigation and adaptation approaches need to be adopted to deal with climate change impact. One way of mitigating climate change is by removing carbon from the atmosphere and storing it in the form of biomass and soil carbon. Thus, increasing the amount of biomass or soil carbon in the forests are viable option to mitigate climate change.

Forests' response to climate change varies. It depends on the characteristics of the tree species and stand structure. Monoculture forests are more vulnerable to climate change compared to mixed forests because of less species diversity and similar stands. Therefore, broad-leaved forests are reported to be more climate resilient than the coniferous forests.

The thesis has revealed the impact of climate change on soil organic carbon, above-ground tree biomass and vegetation shift. However, the impacts of climate change were shown to be positive with AGTB and vegetation shift (i.e. amount of AGTB increases and the area of broad-leaved increases), while negative with SOC (i.e. amount of SOC decreases). On the one hand, it shows that the carbon sequestration capacity of the forests and carbon emissions from the soil is likely to increase along with climate change in the future. On the other hand, the existing forests are likely to become more climate resilient in the future.

The conclusions of this thesis were made based on climatic variables. Other variables, such as human disturbance, natural disturbance, and extreme events also influence the amount of SOC and AGTB, and vegetation shifts. Therefore, future studies should include these variables to understand the future impact on SOC, AGTB and vegetation shift from the perspective of climate change. We also recommend future studies on total carbon emission from the soil and total carbon sequestration in the form of biomass under climate change scenarios to understand the total change in atmospheric carbon.

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Annex-1 Scientific articles and personal contribution

Scientific articles

1. Malla, R., Neupane, P.R and Köhl, M. 2022. Modeling soil organic carbon as a function of topographic and stand variables. *Forests*, 13: 1391. https://doi.org/10.3390/ f13091391
2. Malla, R., Neupane, P.R and Köhl, M. 2023. Assessment of above ground biomass and soil organic carbon in the forests of Nepal under projected scenario. *Frontiers in Forests and Global Change*, Vol 6:1209232. https://doi.org/10.3389/ffgc.2023.1209232
3. Malla, R., Neupane, P.R and Köhl, M. 2023. Climate change impacts: vegetation shift of broad-leaved and coniferous forest. *Trees, Forests and People*, Vol 14:100457. https://doi.org/10.1016/j.tfp.2023.100457

Personal contribution:

The published scientific papers, together with the comprehensive summary, in the cumulative dissertation reflect a substantial part of my scientific research. This is reflected formally by the lead-authorship for all the papers. This includes data processing, the development of methodologies, statistical analysis, the writing and submission as well as the responsibility for the review process of each article. However, the contributions of the co-authors of the papers shall not be questioned. Further research papers are listed in Annex III. None of the scientific papers presented here have been or are currently part of another cumulative dissertation.

Annex II: Letter of contribution to the peer-reviewed articles in the cumulative dissertation

1. Malla, R., Neupane, P.R and Köhl, M. 2022. Modeling soil organic carbon as a function of topographic and stand variables. Forests, 13:1391. https://doi.org/10.3390/ f13091391

   The contributions of the authors to the first peer-reviewed article in the cumulative dissertation were as follows:

   R.M., developed the study design, P.R.N. and M.K. commented on the study design. R.M. was responsible for data acquisition, data analysis, and drafting the manuscript. P.R.N. and M.K. commented on the draft and contributed on writing the final version of the manuscripts. All authors have read and agreed to the published version of the manuscript.

2. Malla, R., Neupane, P.R and Köhl, M. 2023. Assessment of above ground biomass and soil organic carbon in the forests of Nepal under projected scenario. *Frontiers in Forests and Global Change*, 6:1209232 https://doi.org/10.3389/ffgc.2023.1209232

   The contributions of the authors to the second peer-reviewed article in the cumulative dissertation were as follows:

   R.M., developed the study design, P.R.N. and M.K. commented on the study design. R.M. was responsible for data acquisition, data analysis, and drafting the manuscript. P.R.N. and M.K. commented on the draft and contributed on writing the final version of the manuscripts. All authors have read and agreed to the published version of the manuscript.

3. Malla, R., Neupane, P.R and Köhl, M. 2023. Climate change impacts: vegetation shift of broad-leaved and coniferous forest. *Trees, Forests and People,* Vol 14:100457. https://doi.org/10.1016/j.tfp.2023.100457

   The contributions of the authors to the third peer-reviewed article in the cumulative dissertation were as follows:

   R.M., developed the study design, P.R.N. and M.K. commented on the study design. R.M. was responsible for data acquisition, data analysis, and drafting the manuscript. P.R.N. and M.K. commented on the draft and contributed on writing the final version of the manuscripts. All authors have read and agreed to the published version of the manuscript.

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Supervisor: Prof. Dr. Michael Köhl

forests

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Article

Modelling Soil Organic Carbon as a Function of Topography and Stand Variables

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Abstract: Soil organic carbon (SOC) plays a crucial role in global carbon cycling. The amount of SOC is influenced by many factors (climate, topography, forest type, forest disturbance, etc.). To investigate this potential effect, we performed a multiple regression model using six different predictor variables in the third national-level forest resource assessment data of Nepal. We found a significant correlation between the SOC and altitude (r = 0.76) followed by crown cover and slope. The altitude alone explains r^2 = 58 percent of the variability of the SOC and shows an increasing rate of change of SOC with the increase of altitude. Altitude was identified as a suitable predictor of SOC for large areas with high altitudinal variation followed by crown cover and slope. Increasing amounts of SOC with increasing altitude shows the significance of high-altitude forests in the perspective of climate change mitigation. Altitude, a proxy of temperature, provides insights into the influence of changing temperature patterns on SOC due to future climate change. Further study on forest types and SOC along the altitudinal gradient in Nepal is recommended to deal with the climate change problem in the future.

Keywords: altitude; slope; crown cover; soil organic carbon; model; accuracy

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1. Introduction

The SOC is an important carbon pool among the five forest carbon pools [1,2] that plays a crucial role in global carbon cycling [3,4]. It is a vital component of soil and contributes effectively to the functioning of terrestrial ecosystems [5]. Particularly, forest soils comprise about 73% of global soil carbon storage [6]. Therefore, a slight change in the amount of soil carbon may have substantial effects on the atmospheric CO_2 concentration [7].

Forest soils may serve as important carbon sinks for ameliorating excess atmospheric carbon dioxide (CO_2) [8]. SOC levels result from the interactions of major ecosystem processes such as photosynthesis, respiration, and decomposition. Its input rates are primarily determined by the root biomass of a plant including litter that is deposited from plant shoots [9]. The carbon sequestration capacity of soils is affected by biophysical processes such as rainfall infiltration, soil erosion, and soil temperature because of landscape heterogeneity [5]. The soil landscape affects carbon input and carbon losses resulting in a difference in SOC stocks along topographic gradients [8]. The soil carbon dynamics along elevation gradients are usually the product of the long-term interactions between climate, vegetation, and soil type [10].

The amount of SOC in the forests of the Himalayan region is characterized by climate, vegetation, and topography [11,12]. It is a function of several factors including topography, i.e., altitude, slope and aspect [13–15]; above ground biomass [16]; basal area [17]; canopy cover [18]; and climate [4,19]. However, several studies dealing with SOC [13,15,20,21] cover small altitude ranges (150–1961 m, 1800–2500 m, 1060–1230 m, and 1200–2200 m, respectively) and are small-scale studies [22–26]. The SOC distribution along the altitudinal gradient has not been presented consistently. Some studies show a positive relationship of SOC with altitude [27–32] and some studies show a negative relationship [15,33].

An increase in the SOC stock along the higher altitudes could partly be associated with the decreasing temperature due to increasing altitude [34] and reduced soil carbon losses through decomposition of organic matter [10].

Based on these studies, evidence on the dynamics of SOC for a large area with greater altitudinal variability is difficult to obtain from these studies. Appropriate predictor variables are needed to be assessed to predict the dynamics of SOC at the larger (e.g., national) with higher climatic and altitudinal variation. Therefore, Nepal was selected as it is the country with the widest range of altitude in the world.

The unique variation of altitude in Nepal results in distinct physiographic zones ranging from sub-tropics to the tree line, which allows studying the SOC response for a wide range of topography and forest features. The diverse geography allows for investigation along elevation gradients which is a useful approach in studying environmental change and its effect on soil processes [10]. In the context of Nepal, altitude is considered a major factor that has resulted in wide pronounced differences in climatic conditions [35]. The average temperature decreases by 6 °C for every 1000 m gain in altitude [36]. The altitude does not directly influence, but it is an indication of various climatic functions that govern different vegetation and soil formation processes [37].

Therefore, this study intends to assess the relationships between the SOC and biophysical factors in the study area covering the pronounced altitudinal variation from sub-tropical lowlands to the Himalayan foothills of Nepal. The study will answer the following research questions. (1) Are topographic and stand variables correlated with the SOC distributed in a large area with higher altitudinal and climatic variation? (2) Which predictor variables (topography and forest stand) are significant to predict the amount of SOC that is distributed in a large area with higher altitudinal and climatic variation? The availability of nationwide SOC data further provides traction for an unprecedented opportunity for this study. The findings, thus, can be inferred for a larger geographical area that is characterized by larger biophysical and geographical variation.

2. Materials and Methods

2.1. Study Area

In Nepal, hills and high mountains cover about 86% of the total land area and the remaining 14% is a lowland that is located at less than 300 m altitude. The altitude varies from 60 m above sea level in the Terai, the lowland stretching from east to west, to Mount Everest, with 8,848 m being the highest peak in the world. Wide altitudinal variations and diverse climatic conditions have produced four main physiographic zones i.e., Terai (lowlands), mid-hills, high mountains, and high Himal [38]. The altitudinal variation results in a wide range of climatic conditions which influence the composition of flora and fauna, [35]. Stainton [39] classified 35 forest types in Nepal which are further broadly categorized into 10 major groups that are based on the altitudinal range [35]. Forests that are found in varied altitudinal ranges have been reported to store soil organic carbon and above ground tree biomass at different levels [40]. The study covered the forested area of Nepal ranging from Terai (250 m) to the tree line area (3993 m). These altitudes were selected based on the soil samples that were collected from the forest area in the third national forest inventory. The details of the study area according to physiographic zones are given in Table 1.

Table 1. Study area descriptions in different physiographic zones in Nepal. Source: [38,40–44].

Descriptions	Physiographic Zones				Remarks
	Terai	Siwalik	Middle Mountain	High Mountain and High Himal	
Major forest types	*Shorea robusta* forest, Terai mixed hardwood	*Shorea robusta*, Terai mixed hardwood	Lower mixed hardwood, *Pinus roxburghii*, Terai mixed hardwood	Upper mixed hardwood, *Quercus*, Lower mixed hardwood	
Biomass (Mg ha^{-1})	190.02	172.21	143.26	271.46	Total above-ground airdried biomass
Stem volume (m^3 ha^{-1})	161.66	147.49	124.26	225.24	
Altitude (m)	63–330	93–1955	110–3300	543–8848	Forest cover lies below 4000 m
Soil	Alluvial deposit	Shallow droughty with low surface infiltration	Glacial deposits	Stony and rocky	
Temperature (°C)	14 to 40	12 to 30	−3 to 40	−18 to 36	Jackson 1994
Annual rainfall (mm)	1138–2680	1138–2671	1091–1898	379–2185	

2.2. Data Collection

The study used National level Forest Resource Assessment (FRA) data that were collected from 2010 to 2014. The FRA adopted a two-phased stratified systematic cluster sampling design that was composed of 450 clusters containing 1,553 Permanent Sample Plots (PSPs) that were allocated systematically in the entire forest area [40]. The forest area was grouped into 5 regions and the data were assessed from the *Terai* region (flat area) to the high *Himal* region (high-altitude land). On the PSPs, tree (e.g., diameter at breast height, total tree height, crown length, species diversity, quality class) and stand level data (e.g., crown cover, slope, aspect, location, altitude) were collected. In addition, four soil pits were established in the cardinal direction (north, east, west, and south) of all the PSPs to collect the soil samples. In each cardinal direction, appropriate size of soil pits within the area of 2 m × 2 m were dug at a 21 m distance from the PSP center (Figure 1). The soil samples were collected from three different horizons (1–10 cm, 10–20 cm, and 20–30 cm) up to the depth of 30 cm from each soil pit dug outside the peripheries of the PSPs [42]. The soil layers up to 30 cm is recommended by IPCC under Tier 1 and Tier 2 for SOC estimation in the soil and this layer stores half of the SOC of the top 100 cm [1].

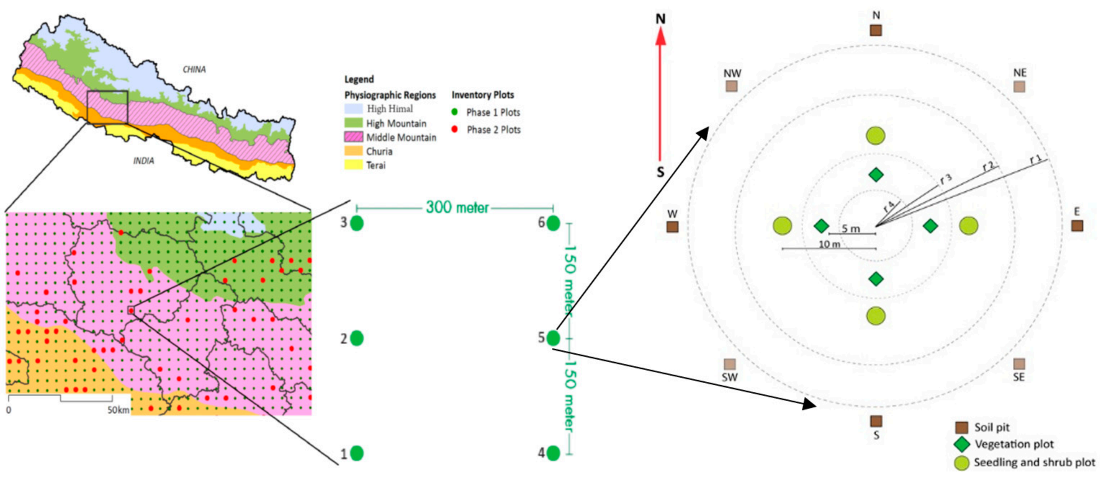


Figure 1. Data collection from the permanent sample plots (PSPs) during forest resource assessment (2010–2014)**.** Source: DFRS/FRA 2014.

2.3. Above Ground Tree Biomass and Soil Organic Carbon Analysis

The former Department of Forest Research and Survey (now Forest Research and Training Center) in Kathmandu, Nepal, analyzed the samples that were collected on the FRA field plots. The above-ground tree biomass (AGTB) was calculated by summing up the stem biomass and branch biomass (Equation (1))

$$\text{AGTB} = \text{Stem biomass} + \text{Branch biomass} \tag{1}$$

Stem biomass was calculated as a product of the volume of the stem [45] and air-dried wood density [46]. Similarly, the branch biomass was calculated using a branch-to-stem ratio that was based on the species type and size of the stem at diameter at breast height [47]. The air-dried wood densities of the tree species ranges from 352 kg/m^3 for *Trewia nudiflora L.* to 960 kg/m^3 for *Acacia catechu (L.F.) wild.* were used.

For SOC analysis, four soil samples of the same horizon of the particular subplots were mixed together. Each subplot had 3 soil samples representing three different soil horizons. The Black wet combustion method [48] was then applied in Department of Forest Research and Survey (DFRS) soil laboratory, Nepal, to analyze soil organic carbon. On the other hand, a dry combustion and LECO CHN Analyzer were used in the Metla Soil Laboratory, Finland, to assure the quality of the laboratory test. Soil organic carbon that was analyzed in the soil laboratory was later estimated on a per hectare basis.

2.4. Variable Selection

The source of SOC is the vegetative matter which is triggered by climatic conditions to decompose it into carbon. Forest variables such as basal area (BA), above-ground tree biomass (AGTB), and crown cover (CC) were utilized. These variables are important to directly describe the vegetative biomass and ultimately help to predict SOC. Similarly, topographical variables such as altitude, slope, and aspect were utilized which are important to describe climatic conditions. Both forest and topographical variables were used as predictor variables of the SOC. Further, multicollinearity among the predictor variables was verified using the *variance inflation factor (VIF)* function in the "car" package of the R program [49]. $VIF > 5$ shows the presence of multicollinearity among the variables [50]. We retained all of the predictor variables in our model as they had $VIF < 5$.

2.5. Data Split

Data analysis was focused on assessing SOC based on topographic (altitude, slope, and aspect) and forest variables (AGTB, basal area (BA), and crown cover). The whole data were split into two sets, i.e., one set of data for developing a model and another set of data for validating the model as an independent dataset. Before splitting the data, a boxplot was used to check the presence of outliers in the data. The outliers were checked for measurement, recording, or lab analysis errors. After error validation, 1032 sub plots from 362 clusters were used for the SOC analysis for ordinary data (non-transformed). For the transformed data, however, 862 PSPs from 311 clusters were used. The transformed data only included PSPs that were located above 250 m altitude as soil sample data below 250 m created non-linearity and heteroscedasticity problems in the linear model. The number of PSPs within clusters ranges from 1 to 6 in lowland and 1 to 4 in highland. The majority of the PSPs representing the highland were spaced 300 m apart and we treated them as independent sample plots for this study. The data were split into two sets i.e., data (80%) for developing models and test data (20%) for data validation. The splitting was done by using the *createDataPartition* function in the "caret" package [51], which splits data randomly into two different sub-sets with different proportions. All data analyses were done in R software [52].

2.6. Modelling

Pearson's correlation analysis was performed to determine the relationship of SOC with six predictor variables (altitude, basal area, AGTB, slope, aspect, crown cover) using the *cor.test* function from the "stat" package in R software [52]. Using the predictor variables, six different models (TM1:TM6) were developed against SOC (transformed SOC data) as a response variable. The predictor variables that were used in the models having higher R^2 values indicate better fits of the models. The presence of heteroscedasticity and normality in the residuals of the models were tested using the *bptest* function (which determines whether the residuals in the linear model are homogenously distributed or not) and the *shapiro.test* function (which determines whether the residuals in the linear models are normally distributed or not) under "lmtest" and "stat" packages, respectively, in R software [53].

2.7. Data Transformation

The models were tested for the assumptions of simple linear regression, i.e., homoscedasticity ($p < 0.05$) and normality ($p > 0.05$). To overcome the problem of rejecting the null hypothesis of the homoscedasticity and normality assumption, the response variable (i.e., SOC) was transformed using the *BoxCoxTransformation* function under "e1071" package in R software [54] to normalize its distribution and six models were developed. The transformation method is used on a non-normal dependent variable to make it into a normal distribution in which statistical tests can be applied.

2.8. Model Validation

An accuracy assessment of the model was conducted to validate the model prediction by using independent test data that had not been used for model development. The predicted value of the response variable was transformed back and compared with the real value that was obtained from the test data. The mean absolute percentage error (MAPE) was used to determine the error percentage of the models to validate the model's accuracy. MAPE was calculated using the *MAPE* function from the "MLmetrics" package in R software [51] (Equation (2)). Lower MAPE values indicate higher accuracy of the models.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - F_i}{O_i}\right| \quad (2)$$

where,

n = number of fitted points
O_i = Actual value of soil organic carbon
F_i = predicted value of soil organic carbon

The accuracy (A) of the model was calculated using Equation (3).

$$A = 1 - MAPE \quad (3)$$

where,

A = Accuracy of the model

3. Results

3.1. Distribution of Variables

Altitude, crown cover, slope, aspect, basal area, and above-ground tree biomass (AGTB) were used as predictor variables to describe the SOC as a response variable. Basic statistics of the variables that were used under study are shown (Table 2). More variability in the variables were seen. This could be due to the sample plots that were recorded throughout the country representing larger climatic, ecological, and altitudinal variations.

Table 2. Distribution of the predictor and response variables.

Variables	Min.	Mean	Max.
SOC (Mg ha^{-1}) *	6.54	62.79	231.72
Altitude (m)	88	1233	3993
Crown cover (%)	4	63.6	99
Slope (%)	0	48	100
Aspect (degree)	0	151	360
Basal area (m2/ha)	0.46	22.1	113.4
AGTB (Mg ha^{-1}) **	1.4	190.02	1306.49

* = oven dry, ** = dry biomass.

3.2. Correlation of Variables

In the correlations and scatterplots of the pairwise combinations of the variables, a strong and linear relationship was found between SOC and altitude ($r = 0.76$, $p < 2.2 \times 10^{-16}$). The correlation between crown cover and slope has also been found significant with SOC. Similarly, a strong but non-linear relationship was found between basal area and AGTB with SOC (Figure 2).

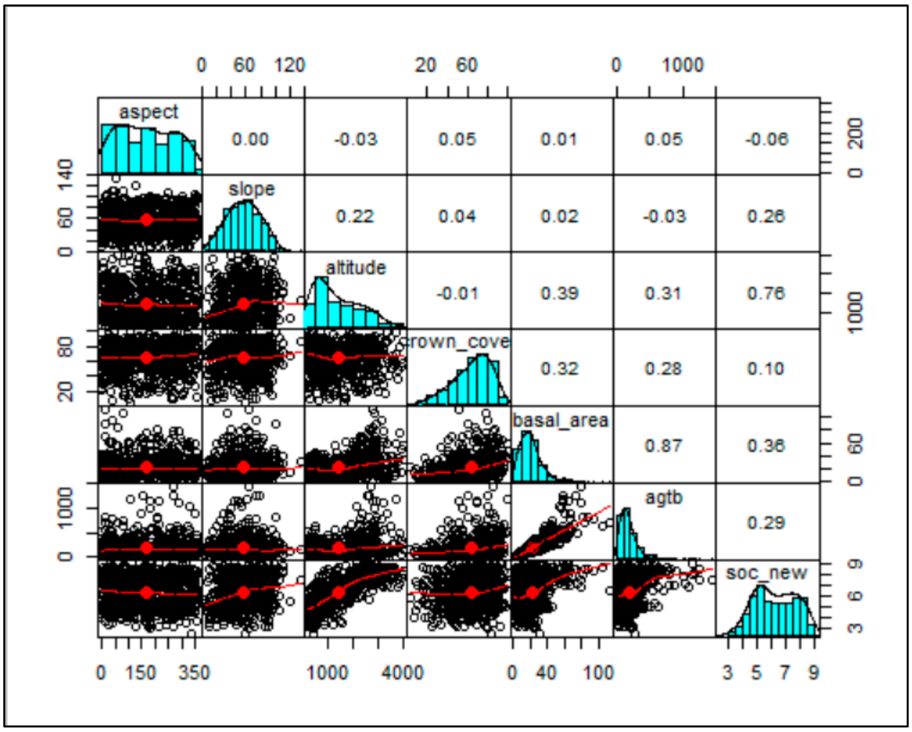


Figure 2. Pairwise correlations and scatterplots of the seven variables i.e., aspect, slope, altitude, crown cover, basal area, above-ground tree biomass (AGTB), and soil organic carbon.

Moreover, the results also shows that there was a significant correlation ($r = 0.87$, $p < 2.2 \times 10^{-16}$) between basal area and AGTB which could cause a multi-collinearity problem when both variables are used together in the model.

3.3. Effects of Topography and Stand Level Variables

As untransformed SOC data in the models did not satisfy the assumptions of linear models, the response variable (SOC) was transformed using the Box–Cox transformation method [54] to normalize the regression models. Box and Cox (1964) developed a family of transformations that were designed to reduce the non-normality of the errors in a linear model [55]. In this model, the output of the model (transformed predicted value) needs to be transformed back to get the normal predicted value (Equation (4)).

$$\text{Normal Predicted value} = \exp(\log(\lambda \times \text{transformed predicted value} + 1)/\lambda) \quad (4)$$

where,

Estimated $\lambda = 0.2$ (It is an "optimal value" that results in the best approximation of a normal distribution).

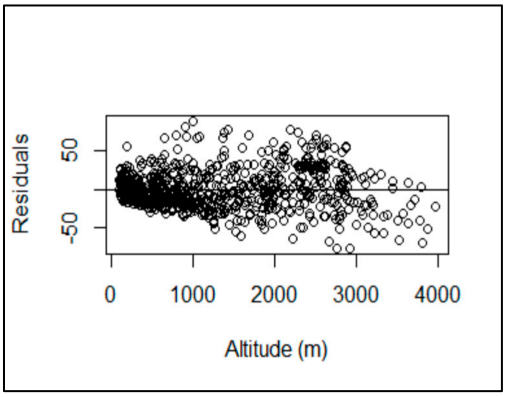
Afterward, six different models were developed which fulfilled the assumption of linear regression models (Table 3).

Table 3. Models after transforming the response variable using the Box–Cox transformation method.

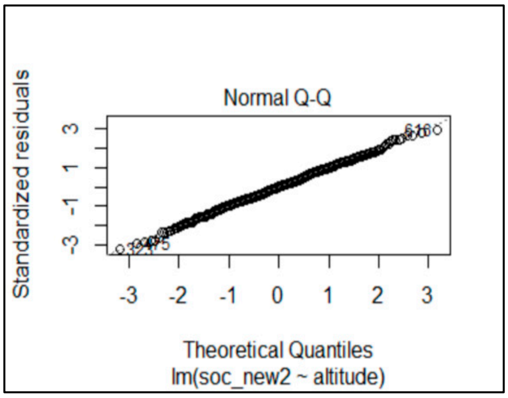
Models	Regression Equations
TM1	SOC = 3.88 *** − 0.0000027(AGTB) + 0.0045(BA) − 0.0006(asp) + 0.0059(slp) *** + 0.0063(cc) *** + 0.0011(alt) ***, where, Adj. $R^2 = 0.602$ and $p < 2.2 \times 10^{-16}$
TM2	SOC = 3.88 *** − 0.0045(BA) − 0.00063(asp) + 0.0059(slp) *** + 0.0063(cc) *** + 0.0014(alt)***, where, Adj. $R^2 = 0.602$ and $p < 2.2 \times 10^{-16}$
TM3	SOC = 3.87 *** − 0.00062(asp) + 0.0056(slp) *** + 0.0075(cc) *** + 0.0011(alt) ***, where, Adj. $R^2 = 0.601$ and $p < 2.2 \times 10^{-16}$
TM4	SOC = 3.77 *** + 0.0056(slp) *** +0.0073(cc) *** + 0.0011(alt) ***, where Adj. $R^2 = 0.599$ and $p < 2.2 \times 10^{-16}$
TM5	SOC = 4.03 *** + 0.0076(cc) *** + 0.0012(alt) ***, where, Adj. $R^2 = 0.592$ and $p < 2.2 \times 10^{-16}$
TM6	SOC = 4.53 *** + 0.0012 alt ***, where, Adj. $R^2 = 0.582$ and $p < 2.2 \times 10^{-16}$

Note: slp = slope, asp = aspect, BA = basal area, cc = crown cover, alt = altitude, Signif. codes: '***' $p < 0.001$.

The residuals of the linear model TM6 show random distribution with mean zero (Figure 3a), and normal distribution and homoscedasticity (Figure 3b).



(a)

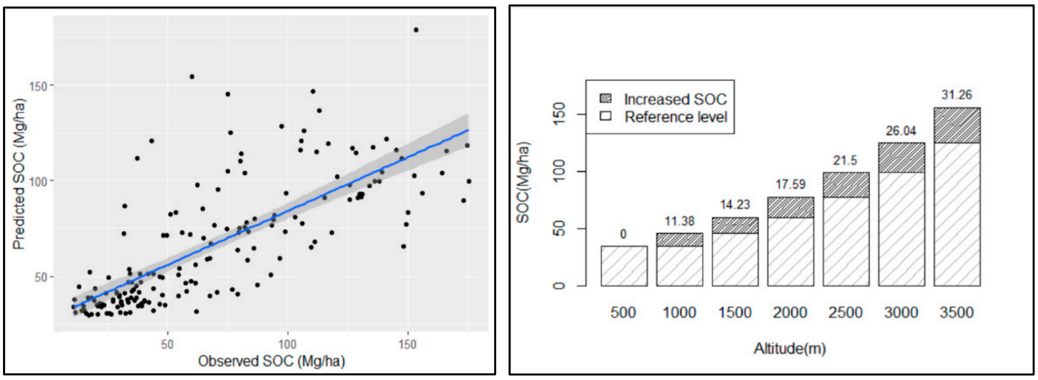


(b)

Figure 3. (**a**) Distribution of the residuals of the model TM6 showing homogeneity; (**b**) standardized residuals in the model TM6 showing normality.

All the parameter estimates for each model were significant at the 0.05 level in the transformed model. Among the six predictor variables in the model (TM1), altitude ($p < 2 \times 10^{-16}$), crown cover ($p < 0.0011$), and slope ($p < 0.00015$) were significant while aspect, AGTB, and basal area were not significant. Among three significant predictor variables, altitude was found to be more significant. The altitude alone as a predictor in the model (TM6) has a significant effect on the SOC (Table 2).

During the transformation of a response variable, the predictor variable (altitude > 250 m) was used by the hit and trial method. Sample plots that were located below 250 m altitude did not show a significant correlation between altitude and SOC. The inclusion of these samples in the models violated the assumption of the linear model (i.e., heteroscedasticity and non-normality), thus they were excluded in the model development. Finally, for all the transformed models (TM1:TM6), the assumption of linear models was accepted i.e., homoscedasticity ($p > 0.05$) and normality ($p > 0.05$). All the candidate models (TM1:TM6) showed similar goodness of fit on the observed data. Better goodness of fit between the observed value and the predicted value of SOC (Figure 4a) and the rate of SOC changes increases with the increase in altitude can be seen (Figure 4b).



(**a**) (**b**)

Figure 4. (**a**) Observed vs. predicted SOC in the model TM6; (**b**) SOC changes in the increase of altitude in the model TM6.

The results show that at every increase of 500 m altitude, the SOC increased by 11.38 Mg ha^{-1} to 31.28 Mg ha^{-1}. Thus, our study confirms that an increase in the SOC amount increases with the increase in altitude (Figure 4b) i.e., the rate of increase of SOC is higher at higher altitudes. Alternatively, the SOC does not increase uniformly with altitude. Instead of proportionality, the change in SOC increases with increasing altitude.

3.4. Accuracy of the Model

Based on the number of predictor variables, TM6—the model with one predictor variable—was found to be an appropriate model for predicting the SOC. Using altitude alone (TM6) provided a similar level of accuracy compared to the other models that used, in addition to altitude, additional predictor variables. In model TM6, the predictor variable altitude was found significant to predict the SOC, producing an accuracy of 67.33% (Table 4).

Table 4. Accuracy of the models.

Models	MAPE (%)	Accuracy (%)
TM1	31.06	68.94
TM2	31.05	68.95
TM3	31.36	68.64
TM4	31.73	68.27
TM5	31.85	68.15
TM6	32.67	67.33

Other variables in the model seemed to be dispensable due to the small accuracy gains. Comparing the results of all the models show that altitude alone (TM6) is the most influential variable to predict SOC with simultaneously maintaining sufficient accuracy with respect to the inclusion of other predictor variables (in TM1:TM5).

4. Discussion

4.1. Distribution of SOC

The storage of SOC is influenced by various factors such as climatic, edaphic and biotic factors [56], and topographic factors [57,58]. In this study, the distribution of SOC concentrates more from the lower elevation region towards the higher elevation region (lower region to high mountain region). This is due to higher altitude-induced low-temperature resulting in lower activities of microbes that are involved in SOM decomposition [59,60]. In Nepal, the average temperature decreases by 6 °C for every 1000 m increase in altitude [36]. A lower temperature is likely to control the retention of SOC [20,61] which shows that the decreasing trend of temperature from lower to higher regions is contributing to higher SOC accumulation. Furthermore, the extraction of forest products (litter, branches, timber) from the forest can also influence the accumulation of SOC due to the reduced availability of forest organic material that can be converted to soil organic matter [62]. Forest product extraction depends on the accessibility of the forest. Accessibility to forests at higher altitudes is difficult due to the rugged terrain compared to lower regions. It is supported by the results that forest disturbances by humans (tree cutting, bush cutting, litter collection, lopping, and cattle grazing) are lower at higher altitudes [40]. Therefore, it can be concluded that the distribution of SOC is likely to be concentrated more on the region with less anthropogenic disturbances compared to a region of higher disturbance [63].

4.2. Effect of Topographic and Stand Variables on SOC

The higher variation in SOC in different sites is due to the variation in topographic, climatic factors, and anthropogenic disturbances. Topographical factors are the main factors contributing to the spatial variability of the SOC [64–66] and induce heterogeneity in SOC which is likely to produce large uncertainties in SOC storage [67,68]. Our study shows altitude as a major significant variable to predict the SOC followed by slope while aspect is insignificant. Aspect has an influence on the local temperature, therefore, microbial activities could be less important. The positive correlation of SOC with altitude implies a negative correlation of SOC with temperature; as altitude increases, the temperature decreases. The formation of SOC mainly depends on the rate of decomposition that is influenced by the temperature; the lower the temperature, the lesser the control on SOC accumulation [20]. A similar trend that was in line with our finding (i.e., positive correlation of SOC and altitude) has been reported in several studies in different regions. e.g., Meghalaya, India (150–1961 m); Brazilian Atlantic Forest (100–1000 m); Mt. Kilimanjaro, Tanzania (750–4000 m); Southern Appalachian, USA (235–1670 m); Saruwaged Mountain, Papua New Guinea's (100–3050 m); Moncayo Massif, SW Europe (1000–1600 m); Mt Changbai, China (700–2000 m); Tropical Montane Forest (1000–3600 m); Bale Mountains, Ethiopia (2390–3250 m); Spain (607–1168 m); and Ethiopia (2034–2410 m) [13,27–32,69–72].

Contrastingly, there are also studies showing decreasing stocks of SOC with increasing altitude [15,33] and no significant relationship between SOC and altitude [73]. These studies were conducted within shorter altitudinal ranges (500–1200 m, 1600–2200 m, 1800–2200 m, 2200–2500 m). Due to the underlying short ranges of altitudes, other variables may have more effect on the SOC. [17] studies SOC in the Mawer Range in India for two attitudinal zones (1800–2200 m and 2200–2500 m) and presents that the mean values of SOC are decreasing with increasing altitude. However, when considering the 95% confidence intervals that were presented by [17], the dissimilarity that was presented was not significant. Altitude does not directly affect the ecosystem but is an indicator of climatic functions [37]. The SOC distribution depends on the altitude-induced variation in climatic variables (temperature, precipitation). The forest soil organic carbon stocks increase with altitude due to slow soil organic matter decomposition at the colder higher elevation sites [70,71].

Our study shows a positive relationship of SOC with slope. The maximum slope that was used in the study was 45° (100%). The increasing slope indicates a higher retention of SOC. Similar findings were reported for slope by [69,74,75] and slope aspect [76]. Land surface temperature decreases with the increase of slope by influencing incidence angle and reflectivity of solar radiation [77], hence a lower rate of decomposition contributing to more SOC retention [20]. Contrary to our findings, [78] found an inverse relationship of SOC with the slope which might be due to the study being confined to a steep and narrow catchment, thereby emphasizing erosive down-hill transport of leaf litter and soil debris.

Moreover, unlike our study, [13] presents a significant effect of aspect on SOC. The study was confined to small areas, so the micro-climatic (local effect) might have an effect on the SOC. Similarly, [68] reports that slope and aspect are major variables that affect the distribution of SOC. The study was conducted within a shorter interval of altitudinal range (i.e., 2400–4000 m), thus slope and aspect could have a strong effect on the SOC. Our study shows that aspect does not hold a strong relationship with SOC in the larger altitudinal variations. The weak relationship between aspect and SOC in the forest area with large altitudinal ranges may be due to the large-scale effect that might filter out the effect of micro-climate.

Similarly, our study gives an indication of the effect of different stand variables (above-ground tree biomass, basal area, and crown cover) on the SOC. Crown cover affects SOC more than above-ground tree biomass and basal area. Crown cover has significant positive correlation with SOC. A similar finding has also been reported by [69]. In fact, tree crown cover helps to reduce soil temperature [79,80]. High crown cover lowers the rate of decomposition of organic matter leading to more SOC retention [20] while an increase in the mean annual temperature decreases the amount of SOC [81]. Relationships between the crown cover and temperature, and between temperature and SOC suggest that maintaining continuous crown cover in the forest contributes to higher SOC accumulation.

Our results did not find a correlation between the above-ground tree biomass and basal area with SOC. On the contrary, a negative correlation between tree biomass (above- and below-ground biomass) and SOC was reported in a case study of community forests in Nepal [82]. Similarly, a negative correlation between the basal area and SOC was reported in the tropical forests of Bangladesh [74]. Contrasting results depict that tree biomass and SOC do not follow the same trend, although the above-ground biomasses are the source of SOC. Tree biomass (tree carbon) is mainly affected by human disturbance and stand structure while SOC is primarily affected by local climate [74]. The disproportionate level of anthropogenic disturbance (tree cutting, forest fire, lopping) along the physiographic regions of Nepal [40] might be a reason for AGTB as a weak predictor for SOC. This was similar the basal area and SOC as basal area and the AGTB were strongly correlated (r = 0.86).

4.3. Altitudinal Effect on SOC and Its Implication

Most of the studies show positive relationship between altitude and the SOC [64,71,83]. Our study also confirms the same relationship by analyzing nationwide data representing a wider variation of altitudinal range from 250 to 3993 m. The results hold good only for the altitudinal ranges that were covered with forests as at some point forest productivity declines and affects SOC accumulation due to climate limitations. In addition, our results show a change in the amount of SOC increases with the increase of altitude. A decrease in the temperature with an increase in the altitude [36] that is accompanied by less anthropogenic disturbance to the forest at higher altitudes [40] could be the reason for SOC accumulation at higher rates at higher altitudes.

The developed model using altitude solely as a predictor of SOC produces two thirds of the accuracy of the model. As such, this can be an option to assess the SOC distribution at the national scale. In addition, the present model gives an avenue to use other predictor variables (along with altitude) including other variables to build more robust models for the estimation of SOC in the future. The phenomena of decreasing temperature with increasing altitude suggests that altitude may be taken as a proxy for increasing temperatures in studies examining the influence of future climate change on SOC. Our study provides a basis for studying the effect of changing temperature patterns due to climate change on soil organic carbon.

Globally, soil alone contains more carbon than the atmosphere and vegetation combined [84]. Thus, a small variation in SOC concentrations can significantly affect the global carbon cycle [85]. Higher altitude forests have the highest biomass density and also store a large amount of SOC in Nepal [40]. According to our results, an increasing rate of change in the amount of SOC with an increase in altitude shows that higher altitude forests are more important from a climate change mitigation perspective. They have been contributing to climate change mitigation by acting as a carbon sink, both with trees and forest soil.

The study covers large areas with a higher altitudinal variation. Such a large-scale study has cancelled out the micro-climatic effect which is very important for small areas for the estimation of SOC. Furthermore, human disturbance of the forest has also a relationship with altitude in a country such as Nepal. The disturbance is directly related to the accessibility (road networks) of the forest; when more the forest is accessible, more is likely to be disturbed. Therefore, altitude can be considered as a proxy of temperature along with human disturbance which shows a confounding effect on SOC stock.

5. Conclusions

The study assessing SOC on the basis of crown cover, slope, and altitude has contributed to a better understanding of biophysical factors that potentially affect SOC, in particular altitude. Our study confirms the positive relationship between SOC and altitude. Particularly, the finding of the study suggests that the rate of SOC accumulation increases with the increase in altitude. However, according to the Third National Communication Report of Nepal to UNFCCC, an increase in temperature is at a higher rate at higher altitude [86] which shows a potential increase in carbon emissions from the forest soil at higher altitudes. With these findings, our study highlights the need for sustainable management of high-altitude forests to maximize the mitigation potential of the forest ecosystems protecting fragile landscapes in Nepal.

Moreover, altitude as a single predictor for large and higher altitudinal variation area, predicted with two thirds of the accuracy for SOC estimation and so could be useful in the future estimation of SOC during national level carbon inventory. Similarly, altitude is an index of climatic functions [37], thus it can be used as a proxy of climatic variables (i.e., temperature). Altitude has possible insights into the influence of changing temperature patterns on SOC due to future climate change. Using the relationship between altitude and SOC, future studies focusing on the SOC distribution under different forest types will provide a better understanding of the contribution of the forest types in climate change mitigation through SOC accumulation.

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Assessment of above ground biomass and soil organic carbon in the forests of Nepal under climate change scenario

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Introduction: Many factors, such as climate, topography, forest management, or tree/forest attributes, influence soil organic carbon (SOC) and above-ground tree biomass (AGTB). This study focuses on assessing relationship between various predictor variables and response variables (SOC and AGTB) in the perspective of climate change scenario. The study was conducted throughout in Nepal using forest resource assessment data (2010–2014).

Methods: Our study applied a random forest model to assess the status of SOC and AGTB under future climate change scenarios using 19 bioclimatic variables accompanied by other variables such as altitude, aspect, basal area, crown cover development status, distance to settlement forest types, number of trees, macro-topography, management regime, physiographic zones, slope, and soil depth. The study used 737 (70%) samples as a training data for model development while 312 (30%) samples as a testing data for model validation.

Results and discussion: The respective RMSE, RMSE% and adjusted R^2 of the Random Forest Model for SOC estimation were found to be 9.53 ton/ha, 15% and 0.746 while same for the AGTB were 37.55 ton/ha, 21.74% and 0.743. Particularly, changes in temperature and precipitation showed an effect on the amount of SOC and AGTB in the projected scenario i.e., CMIP6, SSP2 4.5 for 2040–2060. The study found the amount of SOC decreased by 3.85%, while AGTB increased by 2.96% in the projected scenario. The proposed approach which incorporates the effect of bioclimatic variables can be a better option for understanding the dynamics of SOC and AGTB in the future using climatic variables.

KEYWORDS
biomass, carbon, climate change, random forest model, Nepal, precipitation, temperature

1. Introduction

Forest ecosystems are the largest carbon reservoirs storing ~2 billion tons of CO_2 per year (UNDESA and UNFFS, 2021). The 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines for the national greenhouse gas inventories indicate three major carbon pools (biomass, dead organic matter, and soil) in the forest ecosystem (Eggleston et al., 2006; IPCC, 2006). Most of the forest carbon is found in soil organic matter (45%) followed by living biomass (44%) i.e., above-ground tree biomass (AGTB) and root biomass and remaining in dead organic matter, i.e., in dead wood and litter (FAO, 2020).

Several climatic and edaphic factors influence forest carbon storage (Hofhansl et al., 2020). AGTB is influenced by altitude (Powell et al., 2010; Van der Laan et al., 2014; Rajput et al., 2017), temperature and precipitation (Yan et al., 2015), water availability, soil nitrogen content, and tree cover (Requena Suarez et al., 2021). Similarly, soil organic carbon (SOC) is affected by the amount of above-ground litter fall and root turnover (Andivia et al., 2016), temperature and precipitation (Sun et al., 2019), soil conditions and vegetation (Reyna-Bowen et al., 2019), species diversity (Gamfeldt et al., 2013), soil properties and moisture (Hounkpatin et al., 2018), altitude (Zinn et al., 2018), slope aspect, and soil depths (Zhu et al., 2017).

Climate change is contributing to global warming due to the steady increase in temperature since the 1960s (NOAA, 2023). It is projected to increase the severity of impacts in both the natural and human systems (IPCC, 2023). Climate change, rising temperature particularly, in the future has shown to have a negative effect on AGTB (Larjavaara et al., 2021; Li Y. et al., 2022) and SOC (Kirschbaum, 2000; Zhao et al., 2021) while a positive effect of the rising temperature on AGTB and SOC has also been studied under different climate change scenarios (Fu et al., 2017; Azian et al., 2022). The carbon sink of the forest is sensitive to CO_2 emission change resulting from increasing temperature, hydrological changes, and forest dynamics (Hubau et al., 2020).

Efficient estimation of above ground biomass and soil organic carbon is crucial for the study of carbon dynamics in forest ecosystems. Different assessment methods for the estimation of AGTB and SOC have been carried out. The 2006 IPCC guidelines have provisioned simple to robust method for the estimation of above and below carbon in Tier 1, Tier 2 and Tier 3 categories (IPCC, 2006). Design-based estimation (using ground-based sample plots) is one of the most used approaches for estimating AGTB and SOC (DFRS, 2014, 2015a,b; DFRS/FRA, 2014). Though it provides the precise evaluation of changes (stand structure, tree attributes) due to small standard error (Schadauer and Gabler, 2007), it is time-consuming, less cost- effective and difficult to implement in poorly accessible forest areas (Köhl et al., 2011; Kandel, 2013). Alternatively, a regression model (model-based estimation) has been used for the estimation of AGTB and SOC (Tian et al., 2014; Mohd Zaki et al., 2016; Pokhre, 2018; Li et al., 2019; Malla et al., 2022) that allows more flexibility to provide estimates outside the sample plots (Ståhl et al., 2016). Thus, model based estimation (regression model) is cost-effective and also able to estimate target variables of poorly accessible areas.

Recently, several studies have used a machine learning method such as random forest model (RFM) and gradient boosting (GB) for the prediction of AGTB and SOC (Powell et al., 2010; John et al., 2020; Lee et al., 2020; Li et al., 2020; López-Serrano et al., 2020; Nguyen and Kappas, 2020; Vorster et al., 2020). The RFM model uses machine learning algorithms for classification and regression based on decision trees (Jin et al., 2020). It is appropriate for large datasets with large numbers of variables, non-linear responses, both continuous and categorical variables and is less affected by the multicollinearity problem (Lu et al., 2016). Several studies found RFM superior to the regression model in terms of lowering mean squared error (Hounkpatin et al., 2018; Zhu et al., 2020; Xie et al., 2021), handling non-linear relations (Pahlavan Rad et al., 2014; Hengl et al., 2015), and indifference of assumptions of having probability distribution (normality) and no multicollinearity among independent variables (Lu et al., 2016; López-Serrano et al., 2016). Moreover, RFM does not require several numbers of sample plots, as in the case of design-based estimation, thus it is cost-effective. It can also estimate the target variable of the poorly accessible area in the presence of readily available independent variables (i.e., temperature, precipitation, slope, altitude, etc.).

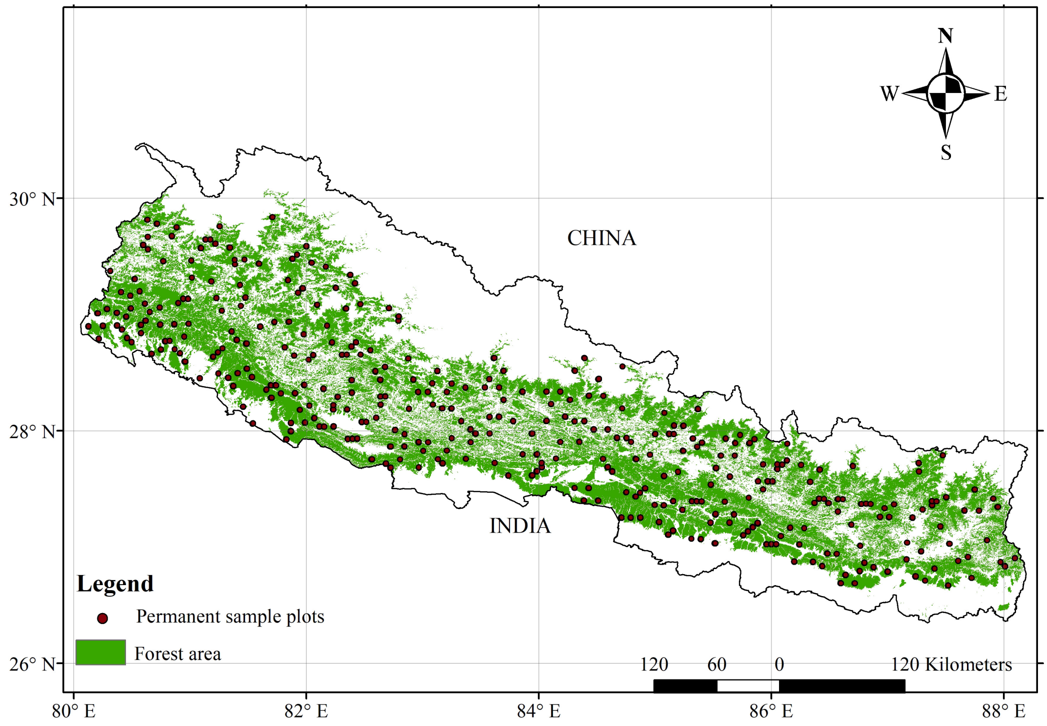
Previous studies have used spectral values of satellite images as an independent variable to predict a response variable such as AGTB and SOC in the past period (Powell et al., 2010; Vicharnakorn et al., 2014; Angelopoulou et al., 2019; López-Serrano et al., 2020; Zhu et al., 2020; Kumar et al., 2022). However, the response of AGTB and SOC against change in climatic variables (temperature and precipitation) in the future has been lacking in the national scenario in Nepal. The influence of temperature and precipitation on the quantity of AGTB and SOC (Mehta et al., 2014; Bennett et al., 2020; Saimun et al., 2021) helps estimate these target variables in future climate change scenarios. Therefore, this study aims to answer the questions (1) Which are the variables (topographic, forest variables and climatic) significant to influence AGTB and SOC? (2) Are these variables likely to contribute to the amount of AGTB and SOC under the climate change scenario? The study covered all the forest covers of Nepal using forest resource assessment data. A RFM was used to better examine the influence of climatic, topographic and forest variables on the amount of AGTB and SOC. The research will improve our understanding of how climate change affects AGTB and SOC in the forests.

2. Materials and methods

2.1. Study area

For this study, we selected Nepal (**Map 1**) as a study site due to its varied site conditions. In Nepal, hilly region occupies a higher chunk of the land (~86% of the total land area) while lowland (less than 300 m altitude) occupies only 14%. Wide altitudinal variations (<300–8,848 m), resulting in diverse climatic conditions, have produced different physiographic zones, i.e., Terai and Siwalik (lowlands), Mid-hills, High mountains and High *Himal* (LRMP, 1986), which influence the composition of flora and fauna (HMGN/MFSC, 2002). Stainton (1972) classified 35 forest types in Nepal that were further broadly categorized into 10 major groups based on the altitudinal range (HMGN/MFSC, 2002).

The climate of Nepal varies seasonally. For the last 30 years (1991–2020), the average monthly temperature ranges from ~ 5°C in January to ~18°C in July, whereas average rainfall ranges from ~20 mm in November to ~340 mm in July (ADB and WB, 2021). Nepal is likely to experience a higher rate of warming in two future periods (2016–2045 and 2036–2065) compared to the reference period, i.e., 1981 to 2010 (GoN/MoFE, 2021) and spatiotemporal changes in precipitation over the period from 1981 to 2010 (Karki et al., 2017). Diverse current and future climatic conditions within comparatively small areas (Dawadi, 2017) make Nepal an ideal place to study the effects of climate change on forests.



MAP 1
Study area map with permanent sample plots within the forest area.

2.2. Data collection

The primary data used in this study were obtained from the third national forest inventory (NFI), which was carried out during 2010–2014. The NFI adopted a two-phase systematic sampling design, composed of 450 clusters containing 1,553 Permanent Sample Plots (PSPs)-after excluding inaccessible PSPs - in the real ground (See **Figure 1**). Data were collected only from the accessible PSPs (slope up to 100 % or 45°). On the sample plots tree related attributes such as diameter at breast height (DBH) and tree height were recorded for the analysis of growing stock, above ground tree biomass and carbon. The third NFI is the first assessment in Nepal that collected soil samples to analyze the SOC of the forests. Four soil pits were established in a cardinal direction in each PSP to collect soil samples. At each cardinal direction, soil pits of appropriate size were dug within the 2 m * 2 m area size at a 21 m distance from the PSP center. In each soil pit, soil samples were collected from three different horizons (1–10 cm, 10–20 cm, and 20–30 cm) up to the depth of 30 cm and were mixed together resulting in 3 soil samples representing three different soil horizons in each PSP (DFRS/FRA, 2014).

Besides forest inventory data, the study used 19 bioclimatic variables representing historic data (near current) representing average figures for the years 1970–2000 at 30 arc sec (~1 km^2) resolution (Fick and Hijmans, 2017). The study also used future climate data from the WorldClim data set[1] at 30 arc sec (~1 km^2) resolution. representing Couple Modeled Inter-comparison Project Phase 6 (CMIP6) based on shared socio-economic pathways (SSP2 4.5) scenario from 2041 to 2060 (i.e., 2050 on average) with resulting global warming of 1.6 –2.5°C (IPCC, 2021). We used this scenario in the study because it is an intermediate scenario among five prescribed by Intergovernmental Panel on Climate Change (IPCC) and is based on the current level of CO_2 emission until the middle of the century.

2.3. Soil organic carbon analysis

Altogether 1,049 PSPs out of 1,553 PSPs were used for SOC analysis. Data from 504 PSPs were removed for one or more of the factors: inappropriateness of the site condition e.g., presence of rock or boulder instead of soil, and missing data for important variables such as aspect, distance to settlement, etc. The Black wet combustion method (Walkley and Black, 1934) was applied in the Nepalese Department of Forest Research and Survey (DFRS) soil laboratory to analyze the SOC content. In addition, dry combustion and LECO CHN Analyzer were used in the Metla Soil Laboratory, Finland, to assure the quality of the laboratory test.

2.4. Above ground tree biomass analysis

Above-ground tree biomass was also estimated from the same PSPs used for SOC analysis. DBH of the tree greater than 5 cm was recorded from the PSPs. The stem volume of the tree was calculated using the equation given by Sharma and Pukkala (1990a).

$$\ln(v) = a + b * \ln(d) + c * \ln(h) \tag{1}$$

1 www.worldclim.org

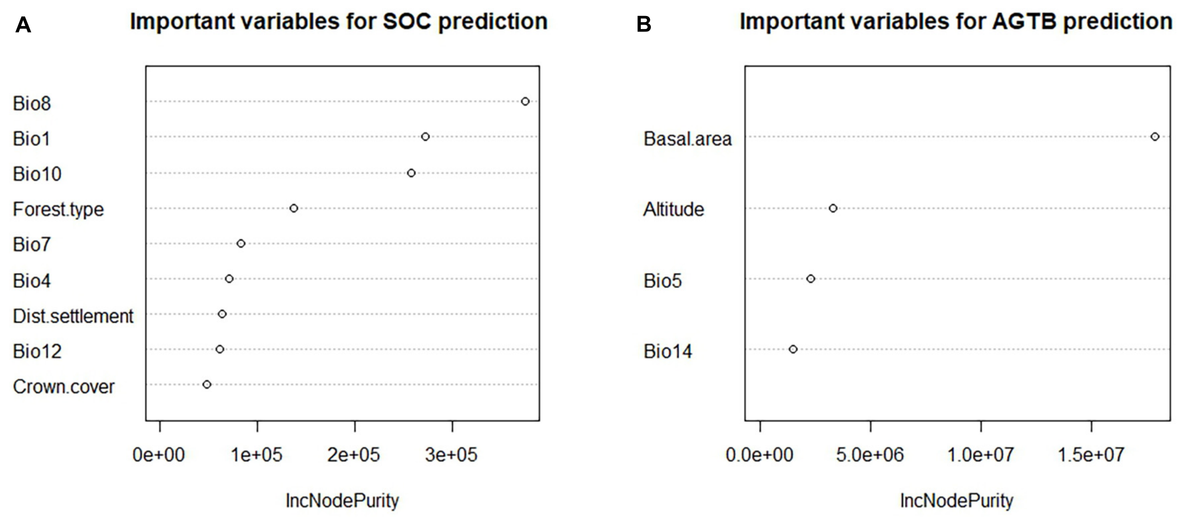


FIGURE 1
Order of variables based on its importance in the models for the prediction of SOC **(A)** and AGTB **(B)**.

where,

ln = Natural logarithm to the base 2.71828,

d = *DBH* in cm.

h = Total tree height in *m*.

a, b and *c* are parameters of the volume equation (**Annex 1**).

To get stem volume in a cubic meter, the model estimation must be divided by 1,000. According to Sharma and Pukkala (1990b), the air-dried wood densities of the tree species range from 352 kg/m^3 for *Trewia nudiflora L.* to 960 kg/m^3 for *Acacia catechu* (L.F.) wild.

In order to estimate AGTB, firstly stem biomass was calculated using following equation.

$$Stem\ biomass\ =\ Volume * Density \quad (2)$$

where,

Volume = Stem volume (m^3).

Density = Air-dried wood density (kg/m^3).

Branch biomass and foliage biomass of the trees were calculated using branch-to-stem and foliage-to-stem ratios, respectively based on tree species and three classes of the size of the stem (small = < 28 cm, medium = 28–53 cm and large = > 53 cm) at diameter at breast height (Sharma and Pukkala, 1990a). Finally, above ground tree biomass (AGTB) of each tree in the PSPs was calculated by using an equation (3). The individual tree biomass (Kg/m^3) within PSP was calculated and it was further converted into ton/ha using the plot expansion factor.

$$AGTB\ =\ Stem\ biomass + Branch\ biomass + Foliage\ biomass \quad (3)$$

2.5. Partition of data set

In order to have independent data sets for model development and model testing, the data were partitioned into two sets A total of 737 (70%) samples were used as training data and 312 (30%) were used as test data. The partitioning of the data was done by using the *createDataPartition* function in the "caret" package (Kuhn, 2008), which splits data randomly into two different subsets with different proportions.

2.6. Variables selection

Altogether 36 variables were identified for modeling purposes (**Table 1**). Out of these 36 variables, we conducted variable selection based on the importance of the variables in the model. To select the important variables, the function *VSURF* from the R package "VSURF" (Genuer et al., 2010) was used. This package selects important predictor variables for the model by step-wise analysis i.e., threshold, interpretation and prediction. Finally, the selected predictor variables were applied in the model development.

2.7. Estimation of SOC and AGTB using random forest model

Estimation of the SOC and AGTB was conducted (including all predictor variables and only important predictor variables) using a random forest model (RFM) by a function *randomForest* under the "randomForest" package in R software (version 4.2.1). RFM is a machine learning tool using bootstrap aggregating to develop models with an improved prediction (Jin et al., 2020). It is based on two parameters i.e., Number of predictor variables (Mtree) and the number of decision trees (Ntree). The random selection of predictor variables and the records in the data set to generate one decision tree helps to achieve higher accuracy in subsequent iterations. In this way, the RFM function generates many decision trees and averages to give an estimation for the response variable. Averaging a large number of decision trees helps to increase accuracy. Moreover, RFM generates *IncNodePurity* which is a total decrease in node impurities when splitting the predictor variables. An increase in the *IncNodePurity* value of the predictor variables

TABLE 1 Variables to be used for the modeling of SOC and AGTB under random forest model.

Variables		Type	Unit	Source
Topographic Variables	Altitude	Numerical	m	FRA, 2010–2014
	Slope	Numerical	degree	
	Aspect	Numerical	degree	
Forest related variables	Crown cover	Numerical	Percent	
	Basal area	Numerical	m^2/ha	
	Number of trees	Numerical	No./ha	
	Above ground tree biomass	Numerical	Ton/ha	
	Development status (4 types)	Categorical	–	
	Distance to settlement	Numerical	m	
	Physiographic zone (5 types)	Categorical	–	
	Macro-topography (6 types)	Categorical	–	
	Forest type (16 types)	Categorical	–	
	Management regime (9 types)	Categorical	–	
	Soil depth (5 types)	Categorical	–	
	Origin (4 types)	Categorical	–	
	Organic layer (5 types)	Categorical	–	
	Soil organic carbon	Numerical	Ton/ha	
Bioclimatic variables	Bio1 = Annual Mean Temperature	Numerical	^{0}C	World clim data 1970–2000
	Bio2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))	Numerical	^{0}C	
	Bio3 = Isothermality (BIO2/BIO7) (× 100)	Numerical	^{0}C	
	Bio4 = Temperature Seasonality (standard deviation × 100)	Numerical	^{0}C	
	Bio5 = Max Temperature of Warmest Month	Numerical	^{0}C	
	Bio6 = Min Temperature of Coldest Month	Numerical	^{0}C	
	Bio7 = Temperature Annual Range (Bio5-Bio6)	Numerical	^{0}C	
	Bio8 = Mean Temperature of Wettest Quarter	Numerical	^{0}C	
	Bio9 = Mean Temperature of Driest Quarter	Numerical	^{0}C	
	Bio10 = Mean Temperature of Warmest Quarter	Numerical	^{0}C	
	Bio11 = Mean Temperature of Coldest Quarter	Numerical	^{0}C	
	Bio12 = Annual Precipitation	Numerical	mm	
	Bio13 = Precipitation of Wettest Month	Numerical	mm	
	Bio14 = Precipitation of Driest Month	Numerical	mm	
	Bio15 = Precipitation Seasonality (Coefficient of Variation)	Numerical	mm	
	Bio16 = Precipitation of Wettest Quarter	Numerical	mm	
	Bio17 = Precipitation of Driest Quarter	Numerical	mm	
	Bio18 = Precipitation of Warmest Quarter	Numerical	mm	
	Bio19 = Precipitation of Coldest Quarter	Numerical	mm	

indicates the higher importance of the variables. Furthermore, the partial dependence plot was plotted using the *partialPlot* function under the "randomForest" package in the R program. The plot shows the marginal effects of predictor variables on the response variable in the model (Friedman, 2001). It is generally used to evaluate whether the relationship between the predictor and response variable is linear, non-linear, or more complex.

2.8. Model validation

Observed data (test data) was plotted against predicted data (model output) to see their relationship for visual interpretation. Moreover, RMSE, RMSE% and R^2 value was calculated to determine the efficiency of the model developed using the *rmse* function ("ModelMetrics" package), *rmse_per* function ("forestmangr" package) and *summary* function in the R program. The RMSE and RMSE% were calculated as follows.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (4)$$

$$RMSE\% = \frac{RMSE}{\bar{y}_i} \times 100 \quad (5)$$

Where,
$\hat{y}i$ = the predicted SOC or AGTB on the i^{th} plot,
yi = the observed SOC or AGTB on the i^{th} plot,
$\bar{y}_i$ = the average value of SOC or AGTB.
n = Number of samples.

3. Results

3.1. Variables used in the model

Altogether 35 independent variables were used for the prediction of SOC or AGTB in the study. Of which, nine variables were selected for the prediction of SOC (Bio1, Bio4, Bio7, Bio8, Bio10, Bio12, Forest type, Distance to settlement and Crown cover) and four variables for the prediction of AGTB (Basal area, Altitude, Bio5 and Bio14).

3.2. Variables importance in the model

The selected 9 and 4 Predictor variables for estimating SOC and AGTB, respectively showed different importance values in the models. The predictor variable "Bio8" was found to be the most important variable for the prediction of SOC followed by Bio1, Bio10, Forest type, Bio7, Bio4, Distance to settlement, Bio12 and Crown cover (**Figure 1A**) whereas Basal area showed its importance highest for the prediction of AGTB followed by Altitude, Bio5, and Bio14 (**Figure 1B**).

3.3. SOC and AGTB estimation

The random forest model was run in two ways. Firstly, all 35 predictor variables (RFM1 and RFM3) were used in the model (RMF1 and RMF3) for the estimation of SOC and AGTB. Secondly, only predictor variables with high-importance values were used in the model (RFM2 and RFM4) for the same estimation (**Table 2**). The root mean square error (RMSE), RMSE% and coefficient of determination (R^2) were found similar for using all 35 predictor variables and using only 9 predictor variables for the estimation of SOC. On the other hand, the performance of the model for the estimation of AGTB was found slightly better while using 35 predictor variables compared to 4 predictor variables (**Table 2**).

3.4. Relation between number of decision trees and error in the model

The number of decision trees (or "trees") in the Random forest model represents the number of sub-samples selected randomly from the original data set. Increasing the number of decision trees helps to reduce the error in the model. The error was sharply reduced when the number of sub-samples selected from the sample population increased from 1 to 100 and slowed down afterward in both the SOC (**Figure 2A**) and AGTB (**Figure 2B**) models.

3.5. Accuracy assessment

Model performance varied in the estimation of SOC (RFM2) and AGTB (RFM4) using test data. RMSE% was found lower in the estimation of SOC as compared to the estimation of AGTB (**Table 3**).

Moreover, the degree of fitness of the model calculated from the predicted value against the observed value for the estimation of SOC was found to be strong i.e., R^2 = 0.759 and the relation was found significant ($p < 0.05$) (**Figure 3A**). A similar degree of fitness was also found in the case of AGTB estimation i.e., R^2 = 0.762 and ($p < 0.05$) (**Figure 3B**).

3.6. Partial dependence plots (Response plots)

Partial dependence plots for each important predictor variable were plotted for both SOC (RFM2) and AGTB (RFM4) models. Our study found that the response variable SOC responded positively with Crown cover, Distance to settlement and Bio12, and responded negatively with Bio1, Bio7, Bio8 and Bio10, whereas it responded both ways (non-linear relation) with Bio4.

An increase in distance to settlement from the forests up to 8,000 m contributed to the increase in SOC, while for longer distances no effect on SOC was found. Similarly, an increase in crown cover and Bio12 also contributed to the increase in SOC. Furthermore, Bio1, Bio8 and Bio10 did not contribute to SOC up to the temperature of 12, 17, and 19°C, respectively. However, the increase in temperature after those limits contributed to a decrease in SOC. In contrast, Bio4 contributed to a decrease in SOC up to 500 mm and afterward, it contributed to an increase in SOC. Lastly, The comparison of forest types revealed that 1, 11, and 17 contributed more to SOC than the other forest types (**Figure 4**).

Above-ground tree biomass responded differently with the four predicted variables (Basal area, Altitude, Bio5 and Bio14). Basal area and Bio5 showed a positive relation with AGTB, while Bio14 and Altitude showed both positive and negative (**Figure 5**). Basal area up to 80 m^2/ha of the forests increased AGTB, and then the

TABLE 2 Summary of the models for the estimation of SOC and AGTB.

Model	Response variable	No. of predictor variable	Ntry	Mtry	RMSE	RMSE%	R^2
RFM1	SOC	35	500	12	9.53	15.00	0.746
RFM2	SOC	9	500	3	10.66	16.77	0.742
RFM3	AGTB	35	500	12	37.55	18.51	0.779
RFM4	AGTB	4	500	2	44.10	21.74	0.743

In the Table, Ntry, number of trees to grow, Mtry, number of variables randomly sampled as candidates at each split, RMSE, root mean square error, R^2, coefficient of determination.

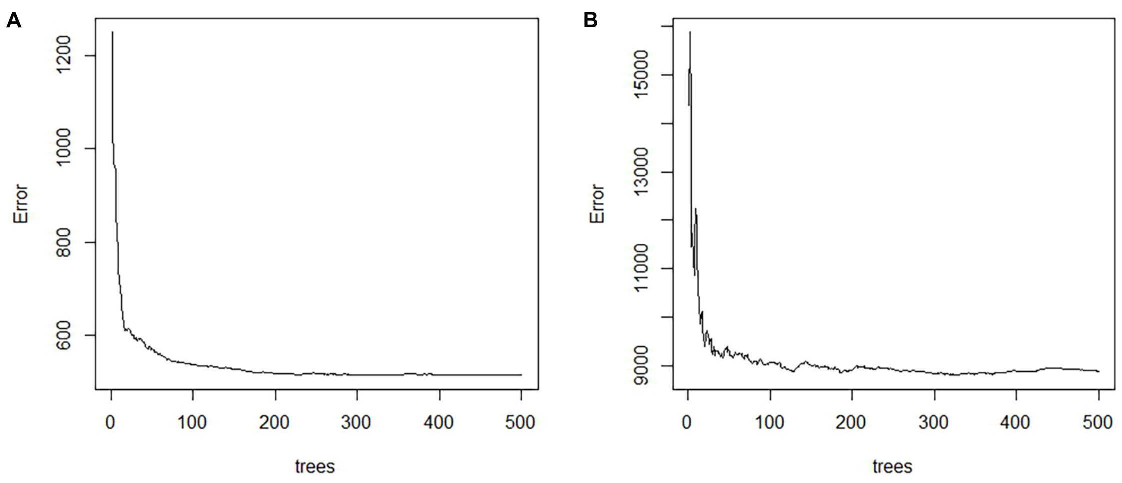


FIGURE 2
Reduction of error as the increase of number of decision trees ("trees") in the RFM2 and RMF4 models for the estimation of SOC **(A)** and AGTB **(B)**, respectively. "Trees" is a number of sub samples selected randomly from the sample population.

amount of AGTB stayed more or less stable, while an increase in Bio5 further increased AGTB. In contrast, altitude and Bio14 decreased AGTB up to 2,000 m and 7 mm, respectively, and after those limits, these variables increased AGTB.

3.7. Amount of soil organic carbon (SOC) and above ground tree biomass (AGTB) using climate change scenario (CMIP6, SSP2 4.5 for 2050)

The CMIP, SSP2 4.5 scenario showed an effect of climate change on SOC and AGTB, assuming other predictors to be the same. An average SOC stock of 63.6 tons/ha was found in the near current period, while it would decrease to 61.15 tons/ha in the future scenario. Unlikely, an average AGTB would increase to 210.57 tons/ha in the future scenario compared to the near current period (204.51 ton/ha). Our result shows that the amount of SOC would likely decrease by 3.85% while AGTB would likely increase by 2.96% in the future climate change scenario (Table 4).

The SOC and AGTB were plotted over the individual PSP. The blue lines in both figures represent SOC/ATGB in the near current period (1970–2000) whereas red lines represent them in the future scenario (2040–2060). The blue line has exceeded the red line indicating decreasing trend of SOC in the future scenario (Figure 6A). But, for the amount of AGTB, a red line has exceeded the blue line indicating the trend of AGTB in the future (Figure 6B).

TABLE 3 Error assessment of the models (RFM2 and RFM4) developed to predict soil organic carbon (SOC) and above ground tree biomass (AGTB).

Errors	SOC	AGTB
RMSE	20.32	90.11
RMSE %	32.63	44.44

RMSE, root mean square error and RMSE%, root mean square error percentage.

4. Discussion

4.1. Performance of the random forest models

A random forest model has been used in this study to estimate SOC and AGTB in the current and future climate change scenario. The RFM has been popular and considered to produce better accuracy than the multiple linear regression (Powell et al., 2010; Hounkpatin et al., 2018). The multiple linear regression approach is though popular, it does not well capture the complex relationships between the forest variables; and soil-landscape relationships subject to non-linear dynamics (Grimm et al., 2008; Chen et al., 2012). The coefficient of determination (R^2 value) produced by

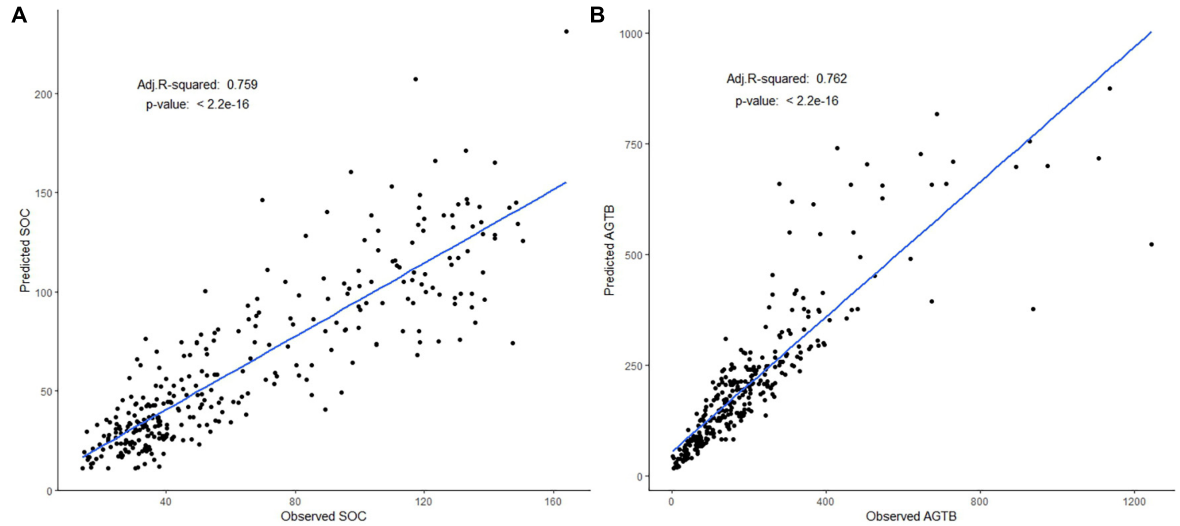


FIGURE 3
Validation of the models for Soil organic carbon (SOC) prediction **(A)** and Above ground tree biomass (AGTB) prediction **(B)** using predicted data and observed data with the help of independent data set.

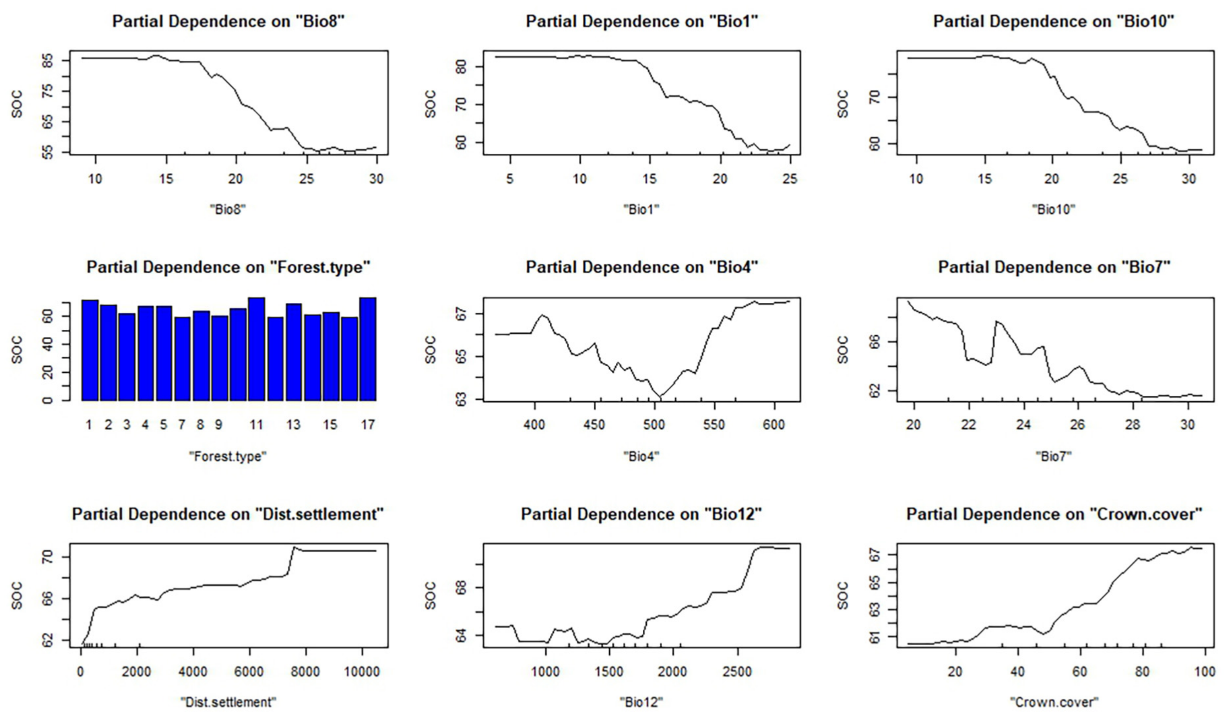


FIGURE 4
Predictor variables responding to Soil organic carbon (SOC) in the partial dependence plot of the random forest model (RFM2) where forest type represented by 1 = Abies spectabilis forest, 2 = Betula utilis forest, 3 = Cedrus deodara forest, 4 = Cupressus torulosa forest, 5 = Junifer wallichiana forest, 7 = Acacia catechu/Dalbergia sisso forest, 8 = Lower mixed hardwood (LMH) forest, 9 = Pinus roxburghii forest, 10 = Pinus wallichiana forest, 11 = Quercus sps forest, 12 = Shorea robusta forest, 13 = Picea smithiana forest, 14 = Shorea robusta TMH forest, 15 = Tsuga dumusa forest,16 = Terai mixed hardwood (TMH) forest, 17 = Upper mixed hardwood (UMH) forest.

our model for the estimation of AGTB is found strong, i.e., 0.74, which is higher than or similar to the other previous studies that used different predictor variables to predict AGTB using RFM (Powell et al., 2010; López-Serrano et al., 2020; Nguyen and Kappas, 2020; Li Z. et al., 2022). Similarly, the RMSE percent of the AGTB model in our study is slightly higher than the results reported by Musthafa and Singh (2022), Wai et al. (2022) and slightly lower than result of Zhu et al. (2020). These studies completely used other predictors (Image pixel value, age, crown density etc.) compared to our studies (especially temperature and precipitation). Moreover,

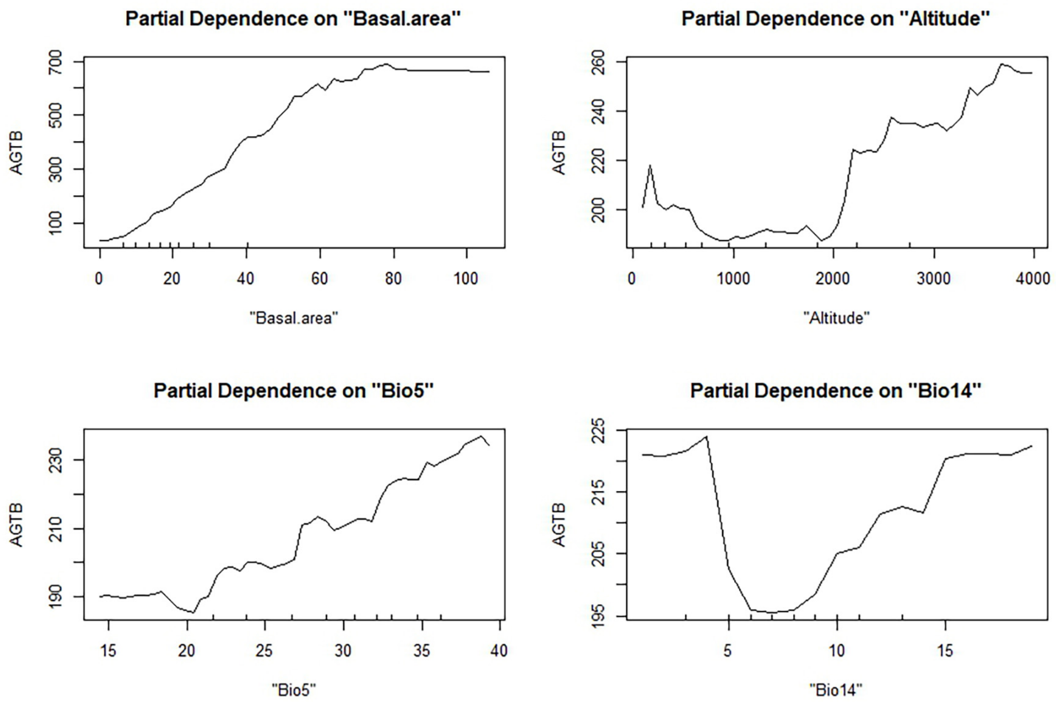


FIGURE 5
Predictor variables responding to above ground tree biomass (AGTB) in the partial dependence plot of the random forest model (RFM4).

TABLE 4 Changes in the amount of soil organic carbon (SOC) and above ground tree biomass (AGTB) in the near current period (1970–2000) and future scenario (2040–2060).

Response variables	Near current period (1970–2000)			Future scenario (2040–2060)			Loss/Gain
	Min	Mean	Max	Min	Mean	Max	
SOC (ton/ha)	12.54	63.6	194.97	18.22	61.15	172.4	−3.85%
AGTB (ton/ha)	5.56	204.51	1121.42	6.04	210.57	1100.14	+2.96%

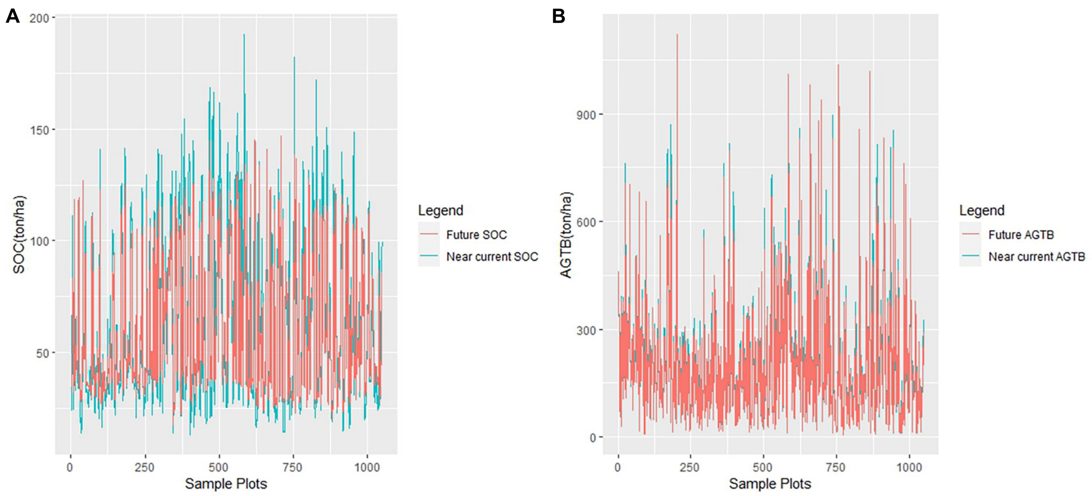


FIGURE 6
Amount of Soil organic carbon (SOC) changes in the future against near current period i.e., 1970–2000 **(A)** and amount of Above ground tree biomass (AGTB) changes in the future against near current scenario **(B)**.

R^2 and RMSE% of the model for the estimation of SOC is smaller and higher, respectively than other studies (Hounkpatin et al., 2018; Lee et al., 2020). The possible reason could be the use of different independent variables in those studies than our study.

If we compare the estimated quantity of SOC and AGTB of the Random forest model with the forest resource assessment result (DFRS, 2015c) based on design based estimation, the quantity is found similar. The estimated average of SOC (63.6 ton/ha) in this study is 4.9% lower than the forest resource assessment result (66.88 ton/ha) whereas the average of AGTB (204.51 ton/ha) is 5.14% higher than the forest inventory result (i.e., 194.51 ton/ha). Though number of samples used in the model is lower than the samples used in design based approach, the Random forest model seems to be capable to produce better accuracy.

4.2. Factors influencing above ground tree biomass (AGTB)

Based on the previous studies, altitude, stand characteristics (tree age, density), slope, aspect, temperature and precipitation affect the AGTB (Powell et al., 2010; Van der Laan et al., 2014; Yan et al., 2015; Zhang et al., 2016; Rajput et al., 2017; Shen et al., 2018). Similar to the other studies (Wang et al., 2017; Bennett et al., 2020; Larjavaara et al., 2021), our study reports the effect of climate attributes on AGTB, particularly due to the maximum temperature of the warmest month (Bio5) and precipitation of the driest month (Bio14).

The RFM used in this study helps understand AGTB as functions of predictors such as altitude and climatic variables. Previous studies also used RFM to estimate AGTB, but were confined to a few predictor variables such as image pixel value, canopy height, topography, vegetation indices, and texture feature (Li Z. et al., 2022; Musthafa and Singh, 2022; Wai et al., 2022).

Our model shows an increase of AGTB under future climate change scenarios, a finding that is consistent with the results reported by Day et al. (2008), Saeed et al. (2019), Wang et al. (2019). Temperature is the most determining climatic factor that helps in accumulation of tree biomass particularly in the growth season (Devi et al., 2020). Similarly, an increase in precipitation in the driest months (Bio14) helps increase AGTB by lengthening the growing season that supports plant growth (Vaganov et al., 1999). Our results show a positive effect of Bio14 and warmer in the summer (similar to Bio5) with AGTB is consistent with the study conducted by Lewis et al. (2013), Devi et al. (2020), Noguchi et al. (2022). Unlike the forests in Nepal, rising temperature is likely to decrease above-ground biomass in the old-growth tropical forests (Larjavaara et al., 2021).

4.3. Factors influencing soil organic carbon (SOC)

Nine predictor variables, including topographic variables, climatic variables, forest types, distance to settlement and crown cover, are important to influence SOC distribution. Previous studies also report similar influencing variables for SOC, topography (altitude, slope and aspect), above-ground biomass, basal area, canopy cover, climate and forest types (Kara et al., 2008; Song et al., 2012; Mohammad and Rasel, 2013; Liu et al., 2016; Bangroo et al., 2017; Chaturvedi and Sun, 2018; Jakšić et al., 2021; Shapkota and Kafle, 2021). Apart from other variables, distance to settlement has also an effect on SOC. Our result shows that an increase in distance to settlement- which is likely to reduce human disturbances- results increase in SOC stock (**Figure 4**). SOC distribution is likely to be more in the area with less human disturbance (Mehta et al., 2008; Eshaghi Rad et al., 2018). Human disturbance such as logging and tree harvest result in a decrease in soil carbon and organic matter (Latty et al., 2004; Moreno et al., 2007).

Our study shows the mean temperature of the wettest quarter (Bio8) as a major predictor variable to estimate SOC in particular. In general, climatic variables are dominating other variables for the prediction of SOC. Similar to our study, previous studies have reported the effect of climate (temperature and precipitation) on SOC (Chen et al., 2015; Alani et al., 2017; Sun et al., 2019; Odebiri et al., 2020; Fang et al., 2022). But, other studies also found altitude as a major variable for SOC prediction (Dieleman et al., 2013; Odebiri et al., 2020). This is also true because altitude though does not directly influence SOC but is an indicator of various climatic functions that govern different vegetation and soil formation processes (Hanawalt and Wittaker, 1976). Thus, altitude can be used as a proxy of climatic variables (Malla et al., 2022).

Furthermore, our model shows a decrease in SOC amount in the future climate change scenario which is similar to the finding reported by Dimobe et al. (2018). Owing to global warming, surface temperature will continue to increase, at least, until 2050 under all emission scenarios (IPCC, 2021). The result shows an increase in temperature (in the future scenario) leads to a decrease in SOC amount, which is supported by other studies (Liu et al., 2021; Zhao et al., 2021). The possible reason could be an increase of soil microbial decomposition due to higher temperature resulting less SOC amount (Dong et al., 2021; Song et al., 2021). Similarly, the negative association of precipitation (in the future scenario) with SOC in our result is similar to the result reported by Alani et al. (2017). The higher amount of precipitation possibly causes to leach dissolved organic carbon of the soil resulting less SOC accumulation.

4.4. Implications of the study

4.4.1. Model implications

Our model shows the effect of climatic variables, topographic variables, forest variables, and distance to settlements on the amount of SOC and AGTB. Particularly, climatic variables (temperature and precipitation) have a direct relation with the formation process of SOC and AGTB. Mean annual precipitation is a driver of the amount of SOC and AGTB (Mehta et al., 2014). Precipitation influences soil moisture and hydrological processes (Heisler and Weltzin, 2006) which is an important factor in SOC cycling (Aanderud et al., 2010) and affects AGTB through functional traits (Cheng et al., 2021). Similarly, temperature also affects the amount of SOC (Zinn et al., 2018; Zhang et al., 2021) and the amount of AGTB (Poudel et al., 2011; Larjavaara et al., 2021). An increase in temperature helps soil microbial decomposition resulting in higher carbon emission or lower SOC accumulation (Dong et al., 2021; Song et al., 2021) whereas warming temperature enhances tree growth resulting in an increase in AGTB (Way and Oren, 2010).

However, most of the previous studies were focused on forest inventory data accompanied by satellite imageries to estimate AGTB and SOC of the latest period (Angelopoulou et al., 2019; López-Serrano et al., 2020). But for the future prediction of AGTB and SOC under climate change scenario, projected bioclimatic variables are necessary as input variables to produce a precise result. These projected bioclimatic variables have been widely used in species distribution modeling, and habitat suitability under different climate change scenarios (Fyllas et al., 2022; Khan et al., 2022; Shrestha et al., 2022) however, the use of these variables have been very limited for SOC prediction (Liu et al., 2021; Zhao et al., 2021).

Inclusion of Bio2 and Bio6 bioclimatic variables with inventory data helps estimate AGTB and SOC, respectively in a better way. Readily available bioclimatic variables not only improve the performance of the model but also reduce the cost of the model. Combining bioclimatic variables with other variables for the prediction of SOC and AGTB can be a viable option to understand the present scenario.

Moreover, using easily available projected bioclimatic variables under different climate change scenarios see text footnote 1 has benefited us in getting a better understanding the trend of SOC and AGTB in the future. Thus, our model shows an advantage over previous model to assess AGTB and SOC in the future climate change scenario using freely available climatic data.

4.4.2. Implications to Nepal

The forest policy of Nepal emphasizes managing forest resources largely through community participation. Almost half of the total forests have been managed under the broad regime of community-based forest management (Ghimire and Lamichhane, 2020). After the involvement of local people in forest resource management, Nepal has received positive changes in the forest condition. The forest cover of Nepal has been in an increasing trend reported by different assessments, i.e., 29% (DFRS, 1999), 40.36% (DFRS, 2015c), 41.69% (FRTC, 2022). Despite these facts, our model shows the amount of SOC is likely to be decreased in the future, whereas there will be a slight gain in the AGTB. In order to increase SOC in the future, the result highlights the need of management intervention to reduce forest degradation and deforestation through sustainable forest management in all the forests of Nepal to deal with climate change impact.

5. Conclusion

Climatic variables (temperature and precipitation) show an effect on the amount of SOC and AGTB in the future climate change scenario. However, the effect of climate on the SOC and AGTB is opposite (positive with AGTB while negative with SOC). Therefore, management intervention through sustainable forest management is crucial in all forest types to maintain SOC level in the future climate change scenario.

Our study proposed an approach for estimating the AGTB and SOC of Nepal using forest inventory data combined with world climate data (bioclimatic variables). Integrating readily available bioclimatic variables along with other predictor variables helps estimate SOC and AGTB in the near current and future scenario, leading to a better understanding of AGTB and SOC dynamics.

Data availability statement

The datasets presented in this article are not readily available because data sets are available from Forest Research and Training Center, Kathmandu, Nepal upon the request of the researchers, students or institutions. Requests to access the datasets should be directed to Forest Research and Training Center, info@frtc.gov.np.

Author contributions

RM contributes on data acquisition, data analysis and drafting manuscript. PN and MK contribute from draft stage to the final stage of the manuscripts. All authors discussed and revised the manuscript and read and approved the final manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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ANNEX

ANNEX 1 Parameters a, b, and c of the volume equation i.e., ln(v) = a + b*ln(d) + c*ln(h).

Species	a	b	c
Abies pindrow	−2.4453	1.7220	1.0757
Acacia catechu	−2.3256	1.6476	1.0552
Adina cordifolia	−2.5626	1.8598	0.8783
Albizia spp.	−2.4284	1.7609	0.9662
Alnus nepalensis	−2.7761	1.9006	0.9428
Anogeissus latifolia	−2.2720	1.7499	0.9174
Bombax malabaricum	−2.3865	1.7414	1.0063
Cedrela toona	−2.1832	1.8679	0.7569
Dalbergia sisso	−2.1959	1.6567	0.9899
Eugenia jambolana	−2.5693	1.8816	0.8498
Hymenodictyon excelsum	−2.5850	1.9437	0.7902
Lagerstroemia parviflora	−2.3411	1.7246	0.9702
Michelia champaca	−2.0152	1.8555	0.7630
Pinus roxburghii	−2.9770	1.9235	1.0019
Pinus wallichiana	−2.8195	1.7250	1.1623
Quercus spp.	−2.3600	1.9680	0.7469
Schima wallichii	−2.7385	1.8155	1.0072
Shorea robusta	−2.4554	1.9026	0.8352
Terminalia tomentosa	−2.4616	1.8497	0.8800
Trewia nudiflora	−2.4585	1.8043	0.9220
Tsuga spp.	−2.5293	1.7815	1.0369
Miscellaneous in Terai	−2.3993	1.7836	0.9546
Miscellaneous in Hills	−2.3204	1.8507	0.8223

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Climate change impacts: Vegetation shift of broad-leaved and coniferous forests

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ABSTRACT

Climate change is a variation in temperature and precipitation for longer periods due to global warming. It has an impact on tree species distribution, composition and diversity of the forests. Our study aims to answer how future climate change is likely to have an impact on the vegetation shift of broad-leaved and coniferous forests. The study used forest resource assessment data (2010–2014) of Nepal to assess vegetation shift from the perspective of climate change scenario. We collected altogether 392 presence points (observations) for broad-leaved forests and 99 for coniferous forests. These occurrence points accompanied by bioclimatic variables and topographical variables (Elevation, Slope and Aspect) were used as input data in a MaxEnt model to predict the distribution of the coniferous and broad-leaved forests. We found a potential area of the near current (1970–2000) coniferous forest replaced by a broad-leaved forest under a climate change scenario (SSP2 4.5 for 2041–2060) and vice versa. The total projected vegetation shift area of Nepal was found to be approximately 1800 km^2 (i.e. over 3 % of the total forest area). Out of the total vegetation shift area, almost 90 % percent of the area was found to be replaced by broad-leaved forest while the remaining 10 % area was found to be replaced by a coniferous forest. The climate change impact has been noticed in the vegetation shift, particularly the presence of broad-leaved forest is more dominant. The study provides better insights into the impact of climate change on the existing vegetation under the future climate change scenario.

1. Introduction

Climate change, a variation in temperature and precipitation regimes, persists for a long period (IPCC, 2013). The global average temperature has increased by 1.1 °C from the period 1850–1900 to 2011–2020(IPCC, 2023) whereas per decade increase of global warming in all the continents has been reported to raise by 0.13 °C during the past 50 years from the period 1948–1998 (Pepin and Seidel, 2005) and the rate is supposed to increase by 0.25–0.48 °C/decade until 2085 (Nogués-Bravo et al., 2007). At the country level, Nepal's warming rate is 0.056 °C/year, with the highest rate of increase in higher altitudes (GoN/MoFE, 2021). The Himalayan region has been reported to have a warming rate approximately 3 times higher than the global average (Xu et al., 2009).

Forest ecosystems are sensitive to climate change and experience changes such as changes in species abundance, forest types, growth rate, structure of forests, tree mortality and tree vitality (Bhatta et al., 2021; Gebeyehu, 2019; Heidenreich and Seidel, 2022; Keane et al., 2020; Kelly and Goulden, 2008b; Taccoen et al., 2022; Thapa and St. George, 2019; Trisurat et al., 2009). Climate change has both positive and negative impacts on forests. Increase in the growth of conifer forests (Wu et al., 2019), an increase in wood production and carbon stock (EGGERS et al., 2008), and an increase in species richness (Zhou et al., 2013) are examples of positive impacts while depletion of the highland ecosystem (Manish et al., 2016), habitat shrinkage of medicinal and aromatic plants (MAPs)(Shrestha et al., 2022) and threatened conifers (Xie et al., 2022), increasing infestation of pest and invasive species (Gebeyehu, 2019) are examples of negative impacts. Climate change studies in Nepal are focused on invasive alien species (Shrestha et al., 2018; Shrestha and Shrestha, 2019; Siwakoti et al., 2016), biodiversity and ecosystem (Bhattacharjee et al., 2017; Paudel et al., 2021; Thapa et al., 2013), medicinal and aromatic plants (Rana et al., 2020; Shrestha et al., 2022), freshwater ecosystems (Lamsal et al., 2017; Singh et al., 2022), human-wildlife- ecosystems interaction (Aryal et al., 2014), and

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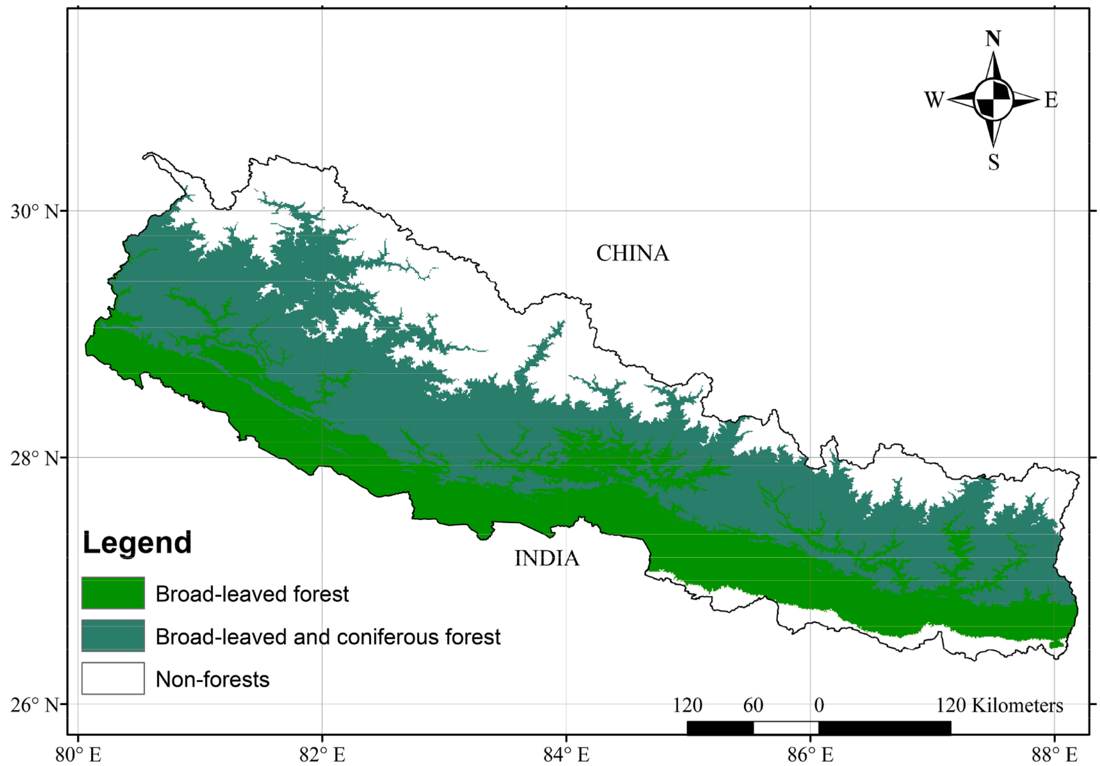

Fig. 1. Map of Nepal showing the distribution of broad leaved and coniferous forests based on the permanent sample plots of forest resource assessment (2010–2014).

Table 1
Forest types information of Nepal.

S. N	Forest types	Altitudinal range (m)	Temperature (°C) (1970–2000)[a]	Precipitation (mm) (1970–2000)	Main dominant tree species	Remarks
1	Coniferous forest	869–3600	−2.7 – 20.5	351 - 2273	*Pinus roxburghii, Pinus wallichiana, Pinus patuala*	Conifers represent more than 60 % of the basal area (DFRS, 2015)
2	Broad-leaved forest	88–3587	2.9 – 24.7	388 - 3215	*Shorea robusta, Castanopsis indica, Schima wallichi, Quercus sps, Rhododendron sps*	Broad-leaved species represent more than 60 % basal area

[a] Mean annual temperature and Annual precipitation from the period of 1970–2000 accessed from www.worldclim.org on 10 June 2022.

Table 2
Environmental variables used in MaxEnt modeling.

Source	Category	Variable description	Unit
United States Geological Survey (USGS)	Topographic	Elev - Elevation	m
		Slp - Slope	Degree
		Asp – Aspect	Degree
World climate	Climatic variable	BIO2 - Mean Diurnal Range (Mean of monthly (max temp - min temp))	°C
		BIO3 - Isothermality (BIO2/BIO7) (×100)	°C
		BIO9 - Mean Temperature of Driest Quarter	°C
		BIO12 - Annual Precipitation	mm
		BIO14 - Precipitation of Driest Month	mm
		BIO15 - Precipitation Seasonality (Coefficient of Variation)	mm
		BIO19 - Precipitation of Coldest Quarter	mm

habitat distribution (Baral et al., 2023; Chhetri et al., 2018; Rai et al., 2022) .

Climate change is causing an expansion of broad-leaved deciduous tree distribution in the boreal forests (Thuiller et al., 2006) suggesting a vegetation shift from coniferous-dominated forests towards broad-leaved species (Hufnagel and Garamvölgyi, 2014; Lindner et al., 2010; Xiao-Ying et al., 2013). In contrast, higher-elevation broad-leaved forest is invaded by lower-elevation coniferous forest in response to climate change (Bai et al., 2011). Both pieces of evidences show a vegetation shift due to climate change taking place in both directions (i.e. Broad-leaved to coniferous and its reverse). The causes of vegetation shift are due to change in the threshold range of the climatic variables, particularly, mean annual precipitation (Zhao et al., 2017), change in climatic variability, particularly drought accompanied by stand structure and topography (Rigling et al., 2013) and increase in CO^2 emission, temperature and precipitation (Hufnagel and Garamvölgyi, 2014).

Climate is considered as a major determinant of forest distribution (Kelly and Goulden, 2008a; Lenoir et al., 2010). In Nepal, the broad-leaved forests are more likely to occur in high -rainfall areas, whereas coniferous forests are confined to low rainfall areas (Bhatta et al., 2021). Presence of broad-leaved forest and coniferous forest under different site conditions, it is important to know the potential impact of future climate change on the adaptive capacity of natural tree vegetation (coniferous and broadleaved forest). Therefore, this study was conducted by combining observational data and model-based approach options to determine the current potential distribution of broad-leaved and coniferous forests and their vegetation shift under future climate

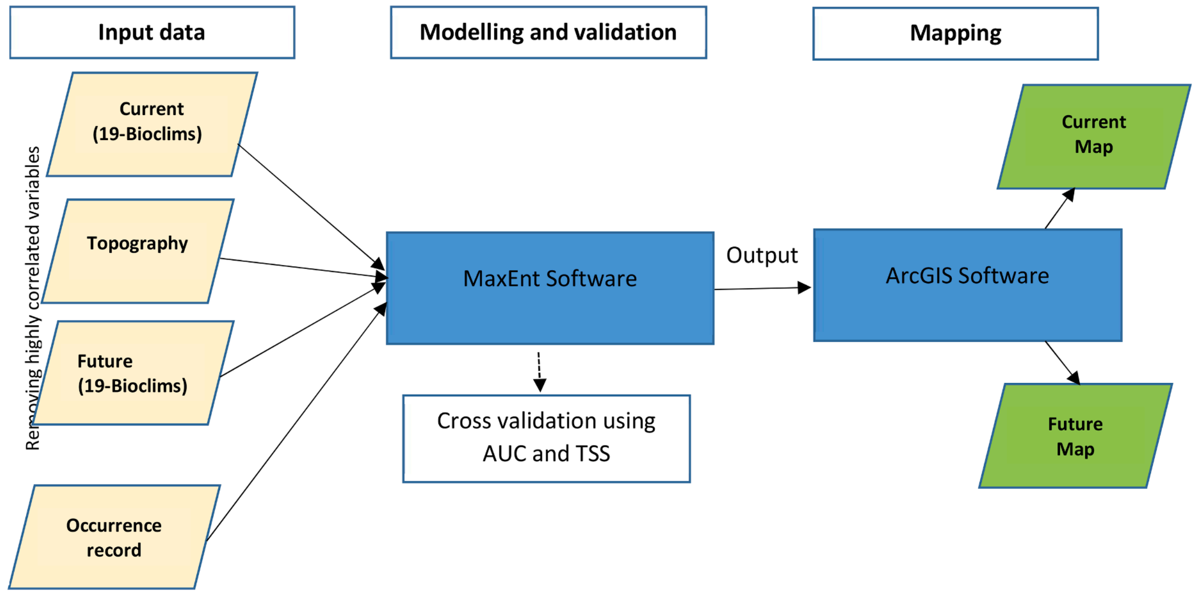

Fig. 2. Flowchart of the methodology used in the MaxEnt modeling and mapping in Arc GIS.

change scenarios. The overarching objective of this study was to explore how broad-leaved and coniferous forests respond to climate change from the perspective of vegetation shift under future climate change scenarios. The study covers all the forest areas of Nepal and intends to improve our understanding of climate change impact on vegetation shift.

2. Methods

2.1. Study area

We conducted this study in Nepal - known as a Himalayan country (latitude 28.3949^0N & Longitude 84.1240^0 E) – that lies between India and China with diverse forest types due to its altitudinal and climatic variations. Stainton (1972) has identified 35 forest types and further grouped them into ten major types[1] based on elevation and species. The distribution of broad-leaved forests occur from the lower region to high mountain region, whereas the coniferous forests are mostly confined to the middle mountain and high mountain regions (DFRS, 2015b, DFRS, 2015a). With the increase in altitude, coniferous forests are replacing broad-leaved forests. The distribution of coniferous forest occurs only in the altitudinal range of 869 m to 3600 m, whereas broadleaved forest occurs throughout the range (Fig. 1). We grouped the forests found in this range into two categories, i.e. coniferous forest and broad-leaved forest (Table 1). The habitats and characteristics of the major forest types within these groups are briefly described below:

2.2. Modeling and mapping

We intended to assess spatial distribution and vegetation shift of coniferous and broad-leaved forest in the future climate change scenario. The potential distribution of the floral and faunal species has been done by using Maximum-entropy (MaxEnt) model in Nepal (Gajurel et al., 2014; Mahatara et al., 2021; Rai et al., 2022; Su et al., 2021). The MaxEnt model, a machine learning algorithm, has been widely used to predict the potential distribution of species [70–72] and also considered a highly performant species distribution modeling algorithm (Elith et al., 2006; Fyllas et al., 2022; Grimmett et al., 2020). We used this model for assessing the potential distribution of the coniferous and broad-leaved forests under future climate change scenarios to better understand climate change impact on vegetation shift.

As an input variable for the model, we used presence points (latitude and longitude) of the forests, topographic variables and climatic variables (projected) which gives distribution map of the forest along with variable response curves in the future climate change scenario as an output. The model used known points and predictor variables to estimate the probability of presence points throughout the study area. We extracted 49 presence points (observations) for coniferous forests and 392 for broad-leaved forests from the forest resource assessment (2010–2014) data of Nepal. In addition, 114 presence points for coniferous forests were extracted from secondary sources (study reports, forest mapping work and visual interpretation) to increase sample points in the study.

We applied a spatial filter of ~1 km x 1 km grid size to maintain at least 1 km distance among the presence points for reducing autocorrelation (Fortin, 1999). Thus, 392 presence points for broad-leaved and 99 presence points for coniferous points were used in this study. Similarly, we downloaded freely available topographical variables (altitude, slope and aspect) from United States Geological Survey (USGS)[2] and pre-processed them in ArcGIS (ESRI, 2017) to prepare in the required format (ASCII), extent, and spatial resolution (30 m).

Moreover, a relatively high resolution of climatic data is appropriate for the area with a diverse climate at a short distance. Therefore, 19 bioclimatic variables (current and projected) were downloaded from world climate data[3] at 30 ′ (~1 km^2). A multicollinearity analysis was performed to remove highly correlated variables ($r > 0.7$) to improve the prediction of the model using *vifstep* function under "usdm" package in R program (Naimi et al., 2023) and remaining 7 bioclimatic variables (Bio2, Bio3, Bio9, Bio12, Bio14, Bio15 and Bio19) were used for the modeling (Table 2). The *vifstep* function calculates the variance inflation factor of a set of predictor variables and excludes highly correlated variables through a stepwise procedure. For the prediction of the

[1] Tropical forest (<1000m), Subtropical broad-leaved forest (1000-2000m), Subtropical pine forest (1000-2200m), Lower temperate broad-leaved forest (1700-2700m), Lower temperate mixed broad-leaved forest (1700-2200m), Upper temperate broad-leaved forest (2200-3000m), Upper temperate mixed broad-leaved forest (2500-3500m), Temperate coniferous forest (2000-3500m), Sub-alpine forest (3000-4100m), Alpine scrub (>4100m)

[2] www.usgs.gov

[3] www.worldclim.org

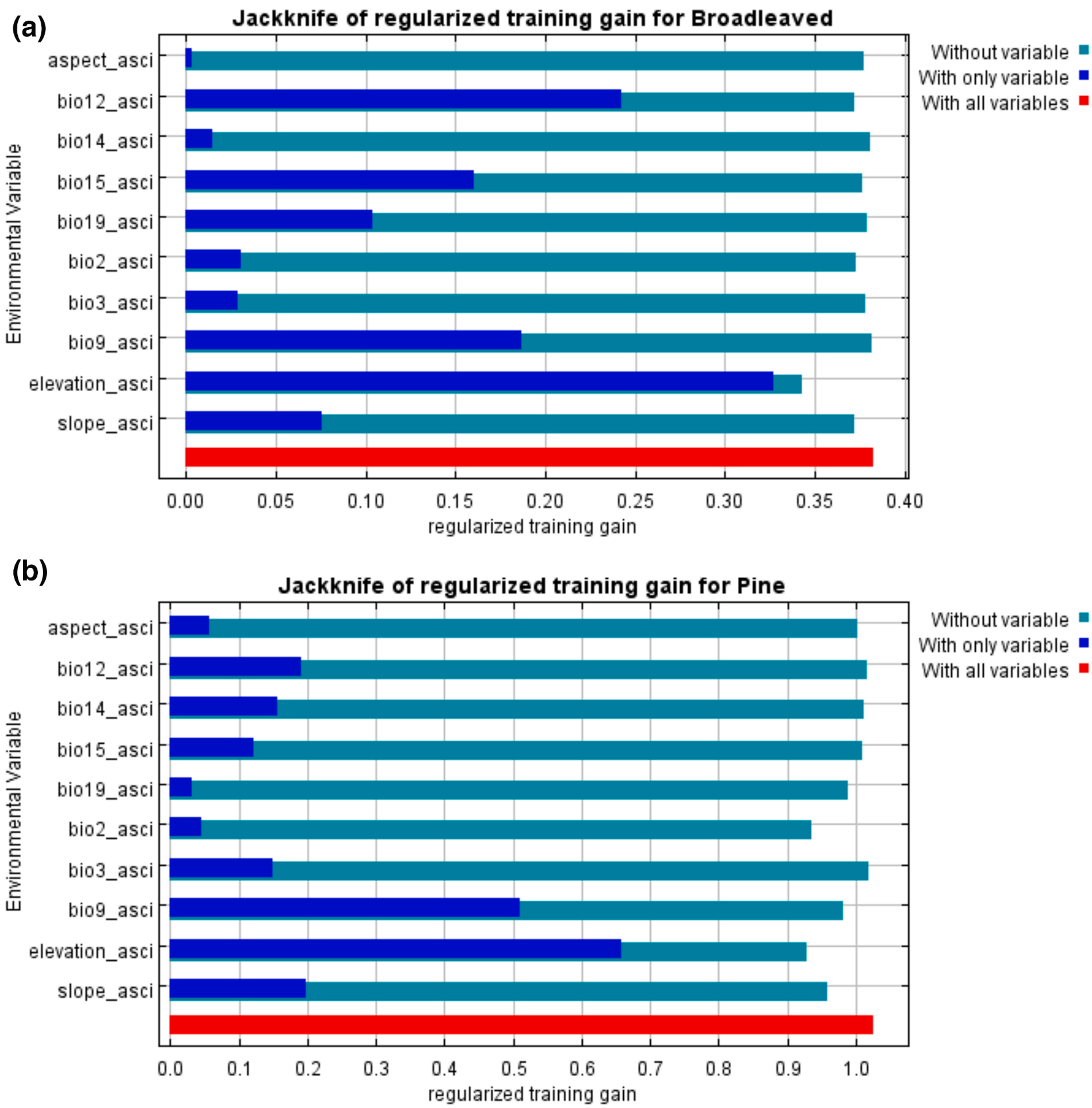

Fig. 3. A Jackknife test of variable importance (regularized training gain) for modeling broad-leaved (a) and coniferous (b) forest distribution based on ten predictor variables.

potential distribution of the broad-leaved and coniferous forests, we used 7 projected bioclimatic variables from MIROC6/GCMs (Global climate models) model under Shared Socio–economic Pathways (SSP2 4.5) scenario for the period of 2041 to 2060 (average 2050).

To run the MaxEnt model in our study, the occurrence points of the forests were examined as a response variable while bioclimatic variables, altitude, slope and aspect as the predictor variables. The model is also used for predicting the distribution of the species in Nepal (Gajurel et al., 2014; Mahatara et al., 2021; Rai et al., 2022; Su et al., 2021). We used 10 replicates (ran the model 10 times) and 1000 background points (points that represent environments or features of the study area) in the model for the prediction (Barbet-Massin et al., 2012) in our study.

The distributions of coniferous and broad-leaved forests in the near current period (1970–2000) and future climate change scenarios (2041–2060) were identified by the MaxEnt software and for further analysis (change in area and spatial distribution) and mapping Arc GIS software was used. We followed steps of building model, its validation and finally preparing map as an output (Fig. 2).

2.3. Accuracy assessment of the models

Accuracy assessment is an important step in the process of developing models that helps validate and evaluate the performance of the model. The 70 % of the occurrence points of broad-leaved and coniferous forests were allocated for the training dataset to develop the models. The remaining 30 % occurrence points were allocated for validating the models. We used two methods to evaluate namely Area under the receiver-operator curve (AUC) which is threshold independent, and True Skill Statistics (TSS) which is threshold dependent. The AUC of models was obtained directly from the model (Phillips et al., 2006; Wiley et al., 2003). Its value, i.e. <0.7, 0.7–0.9 and >0.9, denotes poor model performance, moderately useful model performance, and excellent model performance respectively (Pearce and Ferrier, 2000). Although AUC is a classical and widely used model evaluation parameter, it is criticized by researchers (Lobo et al., 2008). Therefore, in addition, TSS was calculated for the model evaluation (Merow et al., 2013). The value of TSS ranges from -1 to 1, where a value < 0 indicates

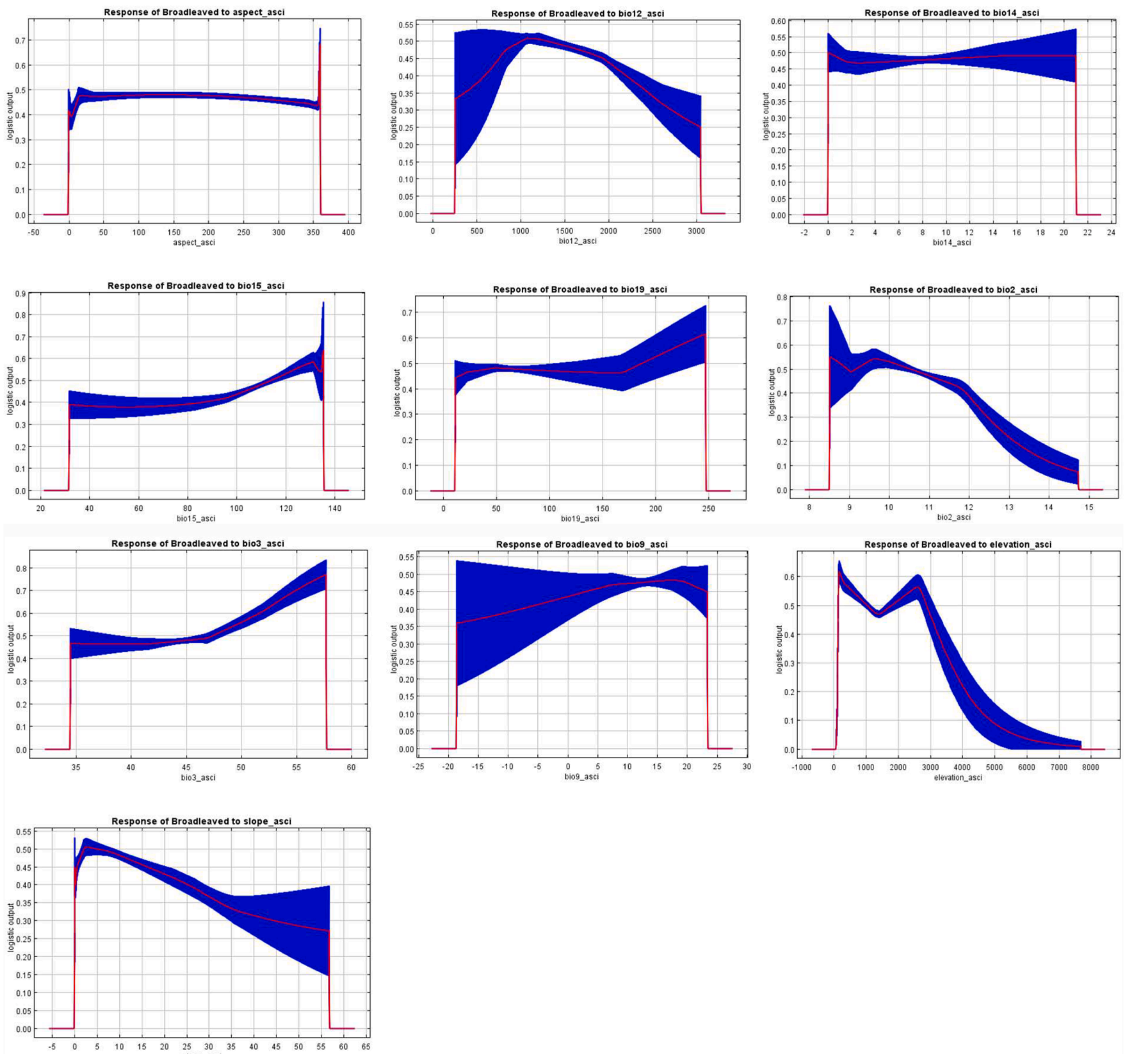

Fig. 4. Response curve of seven bioclimatic and three topographic predictor variables for the distribution of broad-leaved forests. X –axis represents predictor variables, Y- axis represents occurrence probability. Red line represents mean of occurrence probabilities of a predictor variable whereas blue color represents a range of occurrence probability of the predictor variable.

a performance no better than random and 1 indicates a perfect fit of the model (Allouche et al., 2006). TSS was calculated for all model outputs (10 replications), and the final TSS was the average of all 10 replications for coniferous and broad-leaved forests.

3. Results

3.1. *Model performance and contribution of predictor variables in the model*

The MaxEnt model used in our study shows a better distribution of the coniferous forest at near current period (1970–2000) and in the future climate change scenario (2041–2060) than broad-leaved forests. The AUC and TSS of the model for coniferous forests was found to be 0.840 and 0.551 respectively, while for the broad-leaved forests it was 0.698 and 0.311 respectively. According to the relative percent contribution (gain in model when variable is added) of the ten predictor variables, annual precipitation (Bio12) and elevation were the most influential variables in the distribution of both broad-leaved and coniferous forests (Annex1).

Similarly, Fig. 3 shows the variables contribution to the model based on the Jackknife test. The Jackknife test reveals the contribution of the predictor variables on shuffling randomly to observe the effect on the model accuracy (permutation-based importance). Elevation, Mean Temperature of Driest Quarter (Bio9) and Annual precipitation (Bio12) were predictor variables for the distribution of both coniferous and broad-leaved forests while Precipitation Seasonality (Bio15) for broad-leaved forest and Precipitation of Driest Month (Bio14) for coniferous forests.

The result shows that all the predictor variables contributed to the gain of the model. The highest gain of the model by the predictor variable was the "elevation" in both the forests types. It means that when elevation is omitted, it decreases the gain most in the model (Fig. 3).

3.2. *Variables response curve*

The variable response curves of the ten influential variables for the distribution of broad-leaved and coniferous forests are shown in Figs. 4 and 5, respectively. These curves depict how a specific variable responds in the occurrence of the species, while other variables remain unchanged. A response curve with one predictor variable shows the optimal environmental condition that represents the distribution of both forests. The optimal range for example of Annual precipitation (Bio12) i.e.1000–2000 mm, elevation i.e. <1000 m and 2000–3000 m, Mean Diurnal Range (Bio2) –i.e. 8–9 °C was found for the distribution of broad-leaved forests (Fig. 4) whereas the optimal range of Annual

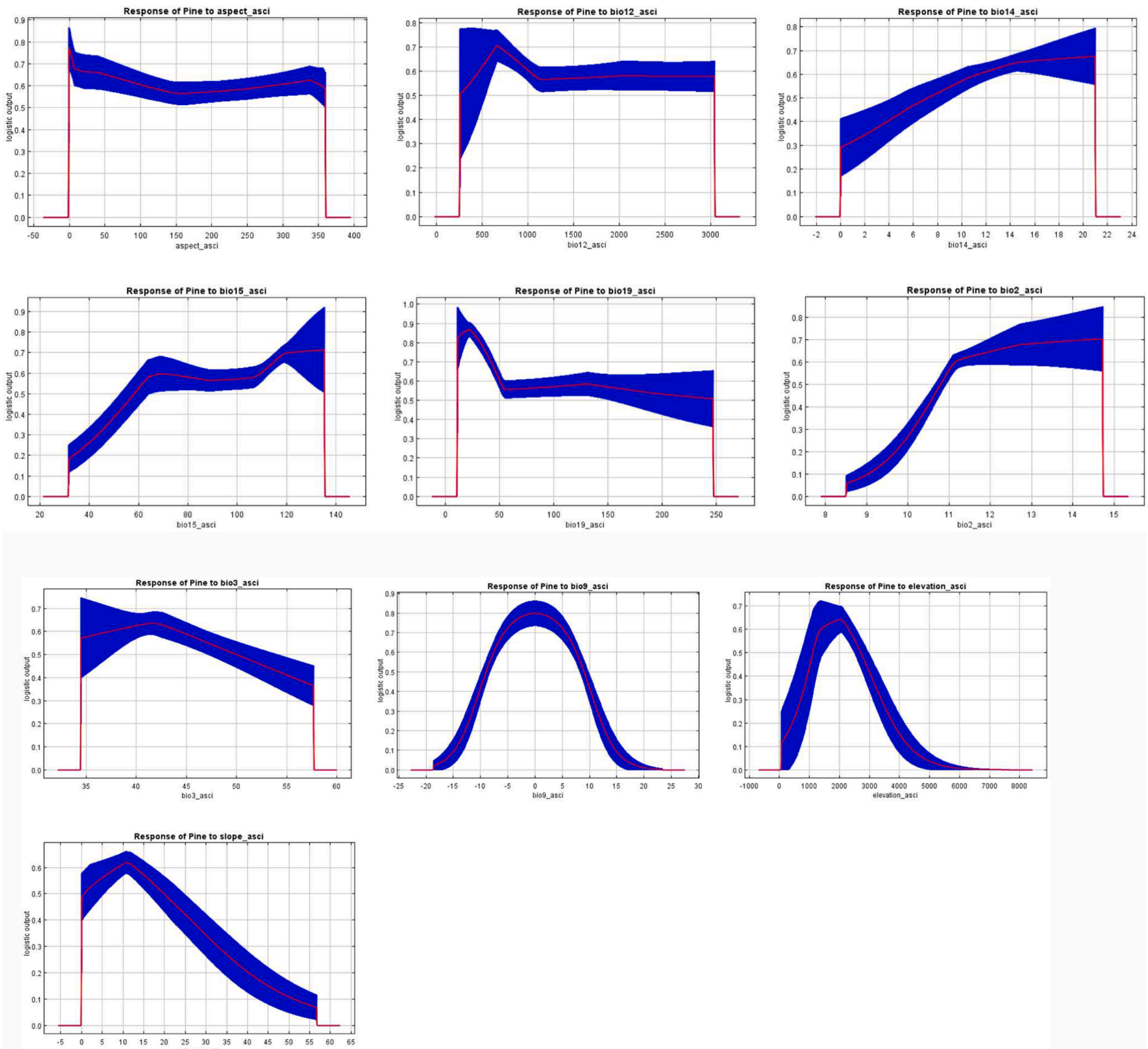

Fig. 5. Response curve of seven bioclimatic and three topographic predictor variables for the distribution of coniferous forests. X –axis represents predictor variables, Y- axis represents occurrence probability. Red line represents mean of occurrence probabilities of a predictor variable whereas blue color represents a range of occurrence probability of the predictor variable.

precipitation (Bio12) i.e.250–750 mm, Elevation i.e. 1000–2000 m and Mean Diurnal Range (Bio2) i.e. 12–14.5 °C was found for coniferous forests (Fig. 5)

3.3. *Distribution of broad-leaved and coniferous forests*

The current distribution of the broad-leaved forests and their future distribution under the climate change scenario (2041–2060) show that these forests are likely to occupy most of the area of Nepal (Fig. 6) in the upcoming decades. In the near current period, the potential distribution of the broad-leaved forests was found to be approximately 90,000 km^2, while its distribution increased by 912 km^2 in the future climate change scenario (Table 4). The result shows that the distribution of broad-leaved forests was found to shift 77 m upwards in higher altitudes (i.e. 3767 m to 3844 m altitude) while no lower shift from the lowest altitude in the future climate change scenario (Table 5).

The distribution of the coniferous forest under the future climate change scenario forests is likely to decrease (Fig. 7). In the near current period, total potential area of the coniferous forest was found to be 43,075.3 km^2 while the area is likely to decrease by 18,020.4 km^2 in the future climate change scenario (Table 3). The result shows that the distribution of coniferous forests was found to shift 54 m lower at the higher altitude (i.e. 4928 m to 4874 m) whereas 214 m higher at lower altitude (i.e. 796 m to 1010 m) in the future climate change scenario (Table 4). Potential area of the coniferous forests distributed in the lower region is likely to decrease more than the higher region in the future climate change scenario (Fig. 7b). It shows that climate change influences habitat shrinkage of coniferous forests occurring in the lower and higher elevation.

3.4. *Climate change impact on vegetation shift*

We found an area of coniferous forests near the current period would be shifted into a broad- leaved forest under the climate change scenario and vice versa. The total vegetation shift area was found to be 1810 km^2 which is more than 3 % of the total forest area of Nepal (Table 5). Out of the total vegetation shift area, almost 90 % percent of the shifted area would be occupied by broad-leaved forests replacing coniferous forests while the remaining 10 % of the area would be occupied by coniferous forests replacing broad-leaved forests (Fig. 8). The vegetation shift of coniferous forests into broad-leaved forests is more dominant than the broad-leaved into coniferous forests under future climate change

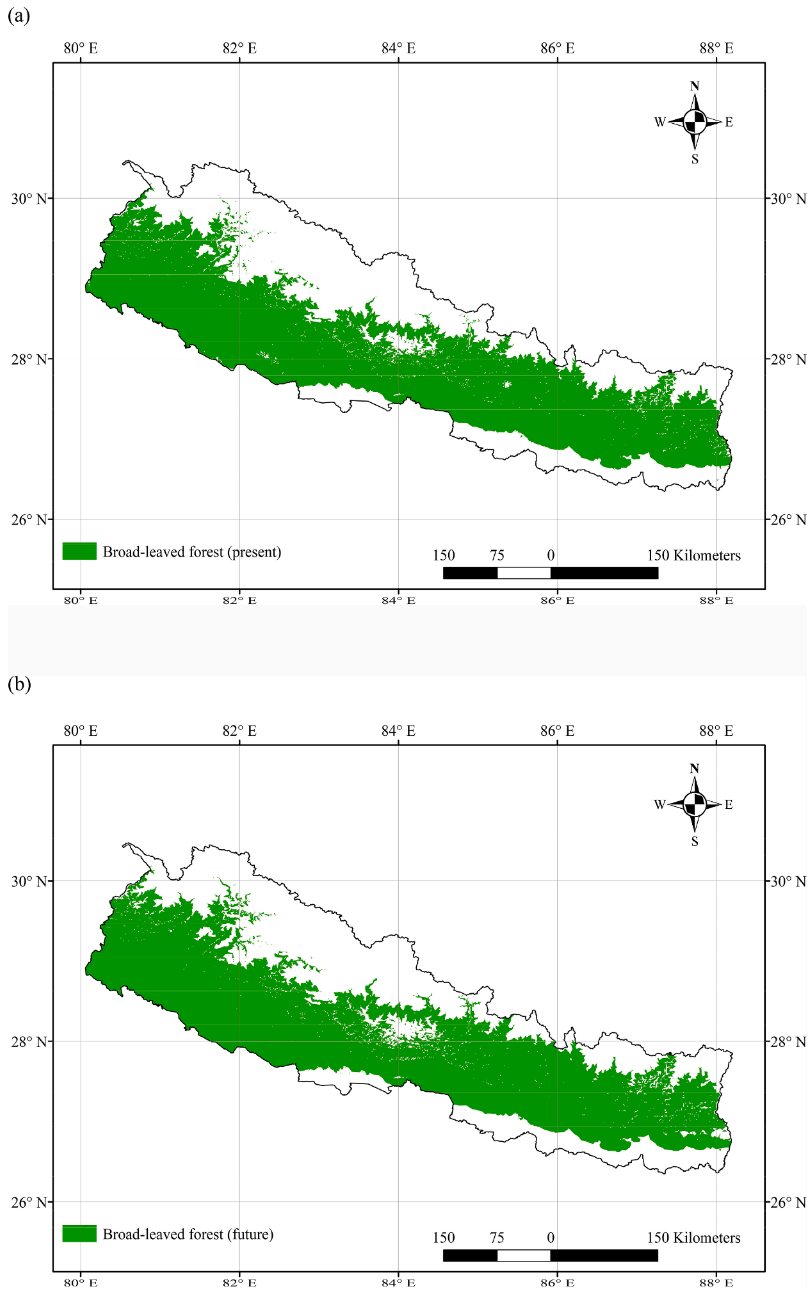

Fig. 6. Potential distribution of the broad-leaved forest at near current (a) and in the future (b).

scenarios. The result shows that climate change is likely to cause a vegetation shift in the future.

4. Discussion

The result shows that coniferous forests are more likely to shift into broad-leaved forest in the future (Fig. 8a), supporting the hypothesis of climate change impact on the vegetation shift, i.e. one vegetation into another In agreement with our study of coniferous forests, (Fyllas et al., 2022) reports that climate change leads to potential habitat shrinkage of the species in the higher elevation. Previous studies also reported the impact of climate change on species composition (Feeley et al., 2011), the upward shift of species (Li et al., 2020; Parmesan and Yohe, 2003), and increasing/decreasing species richness (Adhikari et al., 2018; Zhou et al., 2013). Moreover, human disturbance (i.e., tree harvest) contributes to future species distribution along with climate change (Wang et al., 2019).

The distribution of the broad-leaved forest and the coniferous forest is largely determined by annual precipitation (Bio12) and elevation. Elevation and the annual mean temperature (Bio1) are highly correlated and thus elevation can be used as a proxy for climatic variables (Hanawalt and Wittaker, 1976; Malla et al., 2022). Climatic variability is considered a major driver of vegetation shift. The findings of vegetation shift (broad-leaved to coniferous or vice versa) due to climate change in our study are supported by other studies (Hiura et al., 2019; Rigling et al., 2013; Tian and Fu, 2020). Climatic variables (Temperature and precipitation) are important factors in tree and forest growth (Toledo et al., 2011) However, seasonal temperature and precipitation determine the growth of a tree which is species-specific (Gauli et al., 2022) showing that different tree species respond differently with the changing climate. Forests are sensitive to climate change, thus the spatial distribution of broad-leaved forest and coniferous forest has increased over the past 3 decades but at a different rate (Tian and Fu, 2020)

The spatial distribution of broad-leaved and coniferous forests is

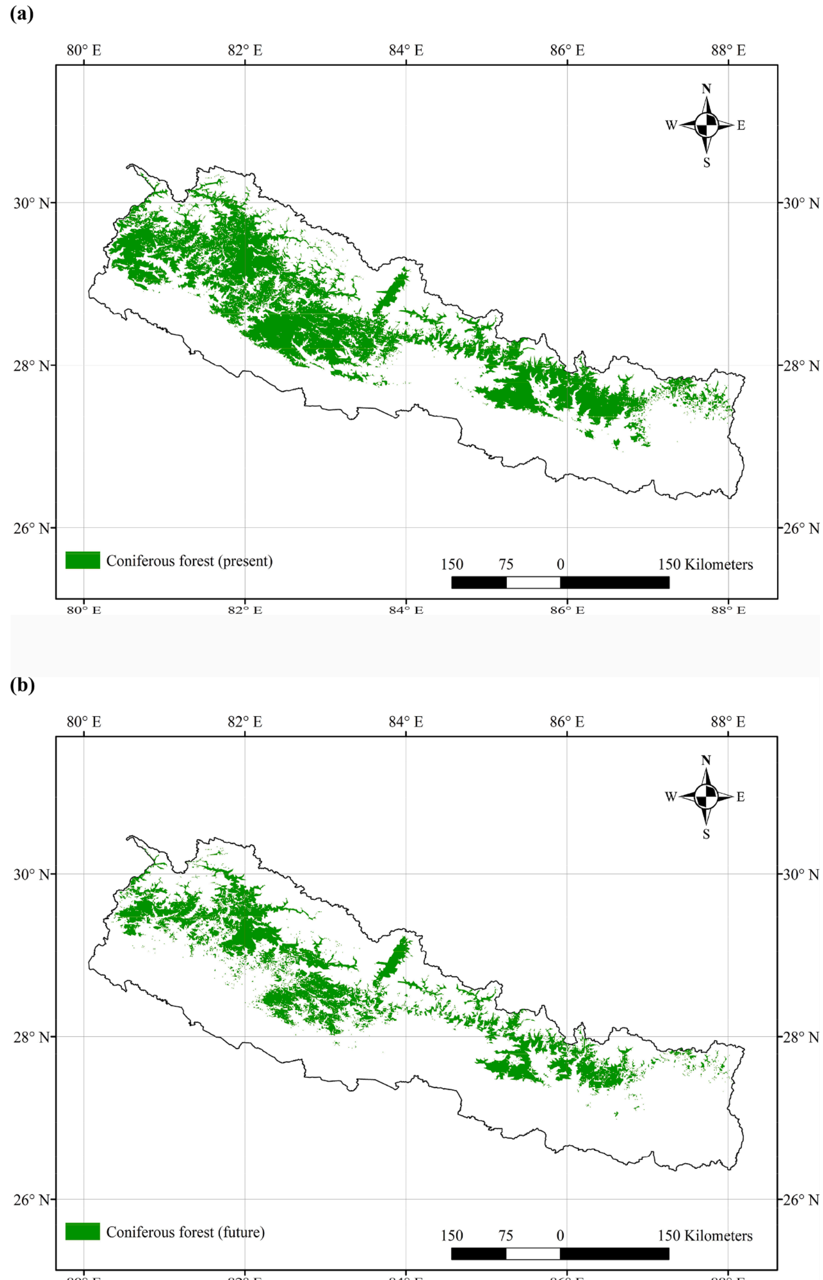

Fig. 7. Potential current (a) and future (b) distribution of coniferous forest.

Table 3
Change of forests area under climate change scenario (2041–2060).

SN	Forests	Suitable areas (km^2)		Change (km^2)
		Near current	Future	
1	Broad-leaved	89,667.09	90,579.17	912.08
2	Coniferous	43,075.3	25,054.9	-18,020.4

different in Nepal. The broad-leaved forests occupy most of the area of the forests compared to coniferous forests. Further, the coniferous forests are confined to the low precipitation area while the broad-leaved forest receives high precipitation (Bhatta et al., 2021) which shows that low precipitation favors coniferous forests more than the broad-leaved forest. In the future climate change scenario (SSP2 4.5 scenario for 2041–2060), the amount of precipitation increases (from 1351.69 mm at the near current to 1418.88 mm in 2041–2060) which could lead to an increased spatial distribution of the broad-leaved forest. Particularly, human-induced global warming acts as a driving factor to increase the frequency, intensity and amount of precipitation (IPCC, 2018)

Table 4
Potential distribution of broad-leaved and coniferous forest at near current (1970–2000) and in the future climate change scenario (2041–2060) with varying altitudinal ranges.

Forest	Current elevation (m)			Future elevation (m)		
	Min	Mean	Max	Min	Mean	Max
Pine	796	2836.93 (1056.58)	4928	1010	2774.67 (933.37)	4874
Broad-leaved	117	1804.32 (976.61)	3767	117	1841.91 (997.23)	3844

Note: Standard deviation shown in parenthesis.

Table 5
Vegetation shift (broad-leaved to coniferous forest and its reverse) in climate change scenario (SSP2 4.5 for 2041–2060.

S.N	Vegetation shift	Area (km^2)	Percentage
1	Coniferous forests into Broad-leaved forests	1578.82	87.19
2	Broad-leaved forests into Coniferous forests	231.90	12.81
	Total	**1810.72**	**100**

Similarly, the temperature increase in future climate change scenarios (from 14.05 °C at the near current to 15.47 °C in 2041–2060) is supposed to favor the expansion of broad-leaved forests. The emission of greenhouse gases due to anthropogenic activities such as burning fossil fuel and forest fires are the main reason to increase global temperature (IPCC, 2018). The lower regions of Nepal are covered mostly with broad-leaved forests (Fig. 6a). Particularly, the increase in temperature is more pronounced in higher altitudes of Nepal (GoN/MoFE, 2021) which supports our findings in the future scenarios, i.e. the upward shift of broad-leaved forests. The change in vegetation shift and geographical distribution may have several possible reasons, but more specifically, it is due to climate change (Parmesan and Yohe, 2003).

The projected vegetation shift in the future climate change scenario will have implications on forest dynamics and the livelihoods of the coniferous forests dependent people. An increasing area of broad-leaved forest in the future climate change scenario leads to an increase in species diversity (Joshi et al., 2022) and an increase in soil organic carbon (Chiti et al., 2012; Joshi et al., 2022) which helps make these forests climate resilient. On the other hand, people dependent on the coniferous forests are likely to be more vulnerable.

Moreover, the MaxEnt model predicts potential distribution of existing vegetation in the study area based on the input data. Potential area of a particular foret vegetation given by the MaxEnt model does not mean that the vegetation exists there but there might be other vegetation or biomes at present. The existing and potential areas of the

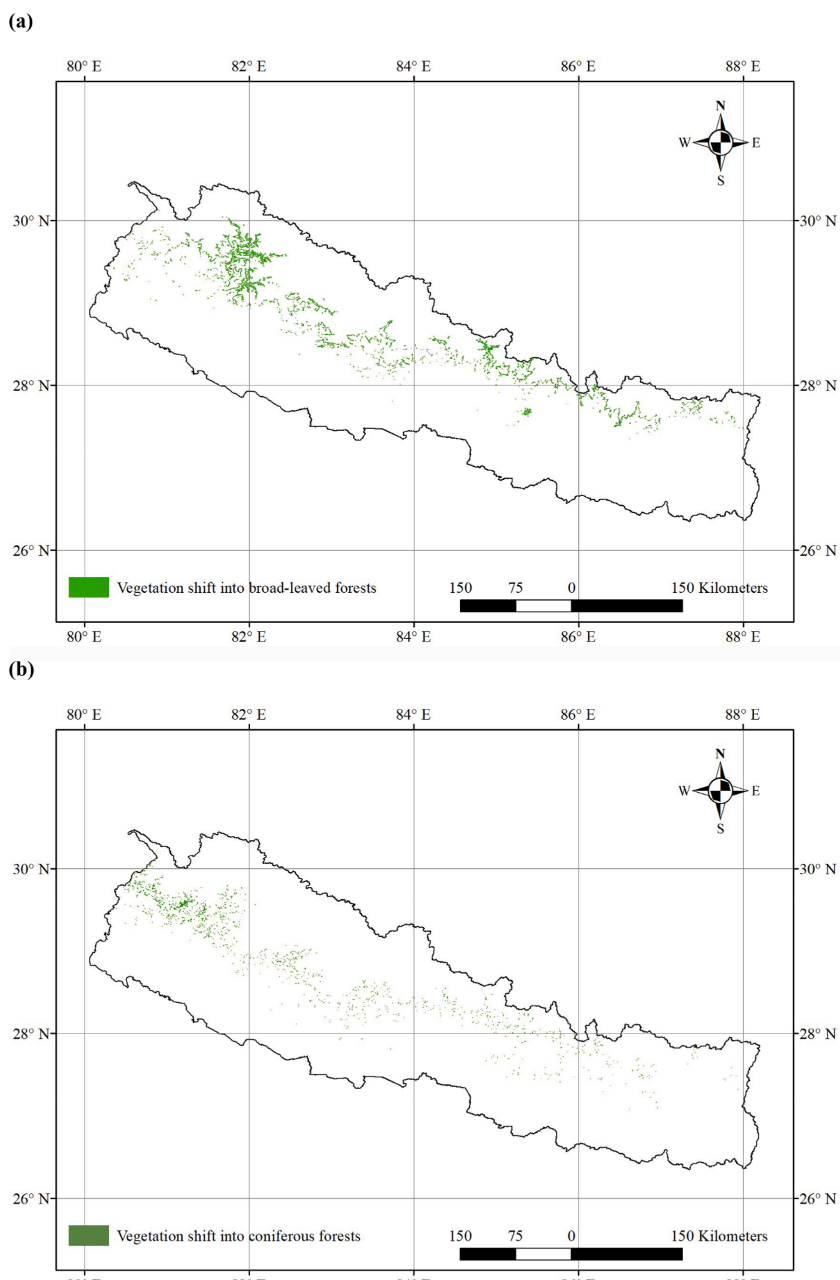

Fig. 8. Vegetation shift from coniferous into broad-leaved (a) and Vegetation shift from broad-leaved into coniferous (b) under climate change scenario.

particular vegetation under study share common environmental conditions which is a basis to predict species distribution. However, negative impact of climate change, such as increased number of fire incidences (Mishra et al., 2023), invasive alien plant species (Shrestha et al., 2018; Shrestha and Shrestha, 2019) and forest pests outbreaks (Pureswaran et al., 2018) accompanied by human disturbances may hinder the vegetation shift differently than the speculation of this study. This study does not provide information on how the transition of forests takes place during the entire process and how climate-induced severe events (forest fire, forest pests/disease, and invasive alien species) and human disturbances affect the vegetation shift process. Depending on the time course of climate change, vegetation shift can occur either abruptly through large-scale mortality events or gently through gradual changes in species abundance. The support of adaptation processes by human intervention must take into account site changes and corresponding changes in potential natural tree vegetation. Especially with the onset of reduced tree vitality and tree mortality, measures for the conservation of current trees or restoration of past species abundances should be critically evaluated based on future potential natural tree species vegetation. Further study on vegetation shift requires climate-induced severe events and human disturbances along with climatic variables for a better understanding the vegetation shift process under climate change scenarios.

5. Conclusion

Climate change in the future scenario shows its impact on the vegetation shift of broad-leaved forests to coniferous forests and vice-versa. However, the vegetation shift from coniferous forest to broad-leaved forest is seen as more dominant. The impact of climate change is not only limited to the area of forest change but is also seen in the altitudinal shift of the newly formed forests. As a result of vegetation shift, it may affect the accumulation of soil organic carbon (SOC), species diversity, and climate resilient capacity of the forest. Vegetation shift to broad-leaved forests under climate change scenario could benefit in terms of maintaining species diversity, and providing multiple-use products and eco-system services. Similarly, vegetation shift from coniferous to broad-leaved forest may negatively affect the coniferous forest dependent local people and forest based enterprises by losing the benefits from the forests in the future.

Availability of data and materials

Data that supports the findings of this study are available from Forest Research and Training Center (FRTC), Kathmandu, Nepal but not publicly accessed due to the data sharing protocol of the FRTC. However, data can be obtained by following formal process of written application with supporting documents.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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Annex1

Relative percent contribution of the predictor variables in the MaxEnt model.

S.N	Variable	Abbreviation	Relative percent contribution Broad-leaved forest	Coniferous forest
1	Annual Precipitation	Bio12	62.3	16.9
2	Elevation	Elev	26.5	55.1
3	Precipitation Seasonality (Coefficient of Variation)	Bio15	2.6	2.1
4	Mean Diurnal Range (Mean of monthly (max temp - min temp))	Bio2	2.5	9.2
5	Slope	Slp	1.9	5.4
6	Precipitation of Coldest Quarter	Bio19	1.8	4.9
7	Aspect	Asp	1.2	2.8
8	Isothermality (BIO2/BIO7) ($\times$ 100)	Bio3	0.8	1
9	Mean Temperature of Driest Quarter	Bio9	0.3	1.9
10	Precipitation of Driest Month	Bio14	0.2	0.7

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Annex III: List of further publications

- **Malla, R** and Acharya, BK. 2018. Natural regeneration potential and growth of degraded *Shorea robusta* (Gaert n.f.) forest in Terai region of Nepal. *Banko Janakari.* 28 (1), 3-10.

- Baral, SK., **Malla, R.,** Khanal, S and Shakya, R. 2013. Trees on farms: diversity, carbon pool and contribution to rural livelihoods in Kanchanpur District of Nepal. *Banko Janakari*. 23(1), 3-11.

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- **Malla, R.**, Panthi ,S., Adhikari, H., Pariyar, S., Baral, R., Subedi, R., Adhikari, BP., Poudel. M., Sedhai, N and Poudel M. 2023. Habitat suitability of four threatened Himalayan species: Asiatic black bear, common leopard, musk deer, and snow leopard. *PeerJ* 11:e16085 https://doi.org/10.7717/peerj.16085