OCCURRENCE, DISTRIBUTION, RESILIENCE OF SOIL ORGANIC CARBON AND ITS DEPENDENCE ON NATURAL AND ANTHROPOGENIC FACTORS

A thesis submitted in partial fulfillment of the requirement for the award of the degree of

Doctor of Philosophy

By

Gilbert Hinge

Department of Civil Engineering

Indian Institute of Technology Guwahati

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Department of Civil Engineering
Indian Institute of Technology Guwahati
Guwahati-781039, Assam, India

Certificate

It is certified that the work contained in the thesis entitled "**Occurrence, distribution, resilience of soil organic carbon and its dependence on natural and anthropogenic factors**" by Gilbert Hinge, Roll Number 156104016, a student in the Department of Civil Engineering, Indian Institute of Technology Guwahati for the award of the degree of Doctor of Philosophy has been carried out under our supervision and that this work has not been submitted elsewhere for a degree.

Dr. Manish Kumar Goyal
Associate Professor
Discipline of Civil Engineering
Indian Institute of Technology
Indore-453552

Date:
Place

Prof. Rao Y. Surampalli
Professor
Global Institute for Energy,
Environment, and Sustainability
Lenexa, Kansas 66285, USA

Date:
Place

Prof. Arup Kumar Sarma
Professor
Department of Civil Engineering
Indian Institute of Technology
Guwahati-781039

Date:
Place

Declaration of Authorship

I, Gilbert Hinge, declare that this thesis titled "**Occurrence, distribution, resilience of soil organic carbon and its dependence on natural and anthropogenic factors**" and the work presented in it has been carried out by me under the supervision of Prof. Arup Kumar Sarma, Dr. Manish Kumar Goyal and Prof. Rao Y. Surampalli, Department of Civil Engineering, Indian Institute of Technology Guwahati. This work has not been submitted elsewhere for the award of any degree.

Gilbert Hinge
Department of Civil Engineering
Indian Institute of Technology
Guwahati-781039

Date:

To

My **Parents**

for their blessing, love and support

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Abstract

Climate change due to global warming is the major concern of the 21st century.The drastic increase of greenhouse gases, particularly carbon dioxide has been identified as the major cause of global warming. There is no single technology that will be able to address climate change but a sum of many initiatives may be one of the effective ways to address climate change. Soil represents one of the largest pool of carbon in the biosphere, and there is a potential to use soil as a sink to sequester carbon, which can be one of the initiatives for countering climate change. However, soil is a very complex ecosystem, and there is extensive open deliberation about the amount of carbon storage in soil, the potential of various sites to store carbon and the role of many factors in controlling the storage and emission of soil carbon.

In this work, we developed an integrated process-based framework using field measurement and modeling to evaluate soil carbon dynamics of selected landuse categories in Northeast India. The study consists of a baseline investigation of soil carbon dynamics and spatial distribution of the study area. The evaluation of SOC stock and the factors controlling its distribution under different landuse type using digital soil mapping approach was the first task attempted in this work. The study evaluates the extent of changes in carbon storage of soil and vegetation as a result of shifts in landuse in the past years as per the standard methodology of IPCC, 2006. An integrated tool in the form of soil quality index was developed to evaluate the effectiveness of prevalent landuse in the study area. As for management option, experimental study using vermicompost and biofertilizer to enhance soil carbon storage and other soil properties was also conducted. An attempt was also made to understand how likely changes in precipitation and temperature will have an impact on soil carbon storage.

From the result of the study, the spatial SOC map distribution indicate that the soil with higher SOC values are generally associated with higher elevation and forest cover. On further investigation, we found that that there is no direct relationship between SOC and elevation.However, elevation had an indirect positive effect on soil carbon. Outcomes of the study show that climate favorability especially higher precipitation and low temperature along the elevation gradient of the forested area were associated with higher plant species richness and plant density, which had a positive effect on SOC. Thus representing the influence of elevation and landuse on SOC. Result also indicated that landuse conversion, particularly the conversion of forest area in the last few years, has resulted in huge carbon losses of both the vegetation and soil of study area. Findings from the study denote that the soil carbon and other soil properties of the study region were highly influenced by landuse and soil management. Results particularly highlight the negative impact of prevalent practice such as shifting cultivation on the soil of the study area. Results of resilience analysis indicated that only 5 agro-climatic zones (out of 14) were resilient to disturbance, indicating a threat to the quality and resilient of the soils of these areas unless sufficient adaptation measures are taken. The study also showed that vermicompost is a suitable carrier of free-living nitrogen-fixing bacteria which when added together can serve as a biological tool in soil C management. This information's will be useful to devise proper management and planning to assure arrant source-sink equilibrium of soil carbon stocks in the future and in the long run.

Keywords: Digital soil mapping,carbon fluxes, landuse, Northeast India, soil organic carbon, soil quality index.

Contents

List of Figures

List of Tables

List of Abbreviation

AIC	Akaike information criterion
ANOVA	Analysis of variance
AS	Abandoned Jhum Land
BEF	Biomass Expansion Factor
BIC	Bayesian information criterion
BC	Bun Cultivation
BD	Bulk Density
CEC	Cation Exchange Capacity
CF	Carbon Factor
DEM	Digital Elevation Model
DF	Dense Forest
DSM	Digital Soil Mapping
EC	Electrical Conductivity
FSI	Forest Survey of India
FYM	Farm Yard Manure
GIS	Geographical Information System
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
ISRO	Indian Space Research Organisation
KS	Kolmogorov-Smirnov
LULC	Landuse and landcover
LUSM	Landuse and Soil Management Systems
ME	Mean Error
MNR	Moderately non-resilient
NBSS	National Bureau of Soil Survey.

NDVI	Normalized Difference Vegetation Index
NE	North East
NPK	Nitrogen Phosphorous and Potassium
NRSC	National Remote Sensing Center
PCA	Principal Component Analysis
PCs	Principal components
PF	Pine Forest
ppb	Parts Per Billion
ppm	Parts Per Million
RF	Random Forest
RMSE	Root Mean Square Error
SAGA GIS	System for Automated Geoscientific Analyses
SC	Shifting Cultivation
SOC	Soil Organic Carbon
SeNR	Severely non-resilient to disturbance
SNR	Slightly non-resilient
SQI	Soil Quality Index
SRI	System of Irrigation Method
SRTM	Shuttle Radar Topography Mission Terrain
TGA	Total Geographical Area
TOC	Total Organic Carbon
TOF	Trees Outside Forest

List of Symbols

Symbols	Description
ΔC	Carbon stock changes annually (t C / yr)
ΔC_{Gain}	Annual gain in carbon stock (t C / yr)
ΔC_{Loss}	Annual loss in carbon stock (t C / yr)
C_{t2}	carbon stock in time t_2
C_{t1}	refers to carbon stock in time t_1
$CAR_{v,a}$	Above ground carbon contents during regrowth of forest type v of age a
CAP_v	Carbon content for mature forest type v
CH_4	Methane
CO_2	Carbon Dioxide
F_I	Fertilizers Impact Factor
F_{Lu}	Landuse Factor
F_{MG}	Land Management Factor
Kg C ha^{-1} yr^{-1}	Kilogram of Carbon per hectare per year.
$L_{fuelwood}$	Loss in carbon due to fuel wood gathering
MSE_{OOB}	Out Of Bag Mean Square Error
N_2O	Nitrous Oxide
R^2	R-squared
SOC_a	Soil Organic Carbon at the soil surface
SOC_b	Soil Organic Carbon at the lower depth
$T_{average}$	Mean annual average temperature
$T_{differences}$	Difference between maximum and minimum temperature

CHAPTER 1

Introduction

1.1 Background

Climate change due to global warming is the major concern of the 21st century. The drastic increase of greenhouse gases has been identified as the major cause of global warming (Lal, 2008). Greenhouse gasses such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxides (N_2O) absorb most of the reflecting long wave radiation emitted by the earth to ensure that the earth maintains a moderate temperature required to support all life processes. However, human activities since the industrial revolution have led to an increase of these gases in the atmosphere(Eggleston et al., 2006). Atmospheric CO_2 concentrations have risen from approximately 280 parts per million(ppm) prior to 1750 to 399.5 ppm in 2014, methane levels from 722 to 1834 parts per billion(ppb) and nitrous oxide levels from 270 to 328 ppb (Edenhofer et al., 2014). In recent years, the concentration of these greenhouse gases has been consistently increasing(Blasing, 2016). Around 72% of the total greenhouse gases emitted is carbon dioxide(CO_2), whereas 18% is Methane(CH_4) and 9% is Nitrous oxide (NO_x) (Baumert, 2005). Carbon dioxide emissions are therefore considered as the major cause of global warming.

Carbon a key element of all living things is continuously being recycled over various spheres of life as either solid, liquid or gas (Mackenzie et al., 1980). The total amount of carbon present on the planet isn't the issue as there is always a fixed amount of carbon. However, human activities such as burning of fossil fuels, deforestation, improper landuse and land management etc. have disturbed the carbon cycle, interrupting the chemistry of where carbon is being stored and climate change is an indication of that alteration(Magnani et al., 2007). Another way of looking at the issues is that lots of carbon that was once being stored in a solid phase are now being converted into a gas (Lal, 2010). For an instant, when fossil fuels are burned, the carbon molecules presence in them combined with two oxygen atoms present in the atmosphere to form CO_2. As a consequence of this, there is excessive carbon present in the atmosphere, too much is being stored in the ocean, but there is insufficient stable carbon, where it once was stored in the soil(Edenhofer et al., 2014).

According to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2007) increase level of CO_2 and other greenhouse concentrations are expected to:

- Elevate the earth's average temperature
- Affect the patterns and intensity of the precipitation
- Raise the sea level
- Deplete snow and ice cover
- Increase the duration, intensity and frequency of various extreme events
- Raise the acidity level of the oceans
- Change the ecosystem characteristics
- Increase dangers to human wellbeing

Therefore, should greenhouse gas particularly carbon emission continue at this rate, the earth's surface temperature will exceed the historical value and will potentially affects our agricultural supply, water supply, biological communities, and even our own well being. Although this is a grim state of affairs, however, there is hope and it is buried right under our feet, in the soil. Indeed soil is one of the largest carbon sinks, where putting additional carbon into it would essentially become beneficial (Lal, 2008). In general, there are five carbon pools viz. oceanic, geological, soil, atmosphere and bio data carbon pools. Soil carbon pool is the third largest carbon pool after oceanic and geological carbon pool. Batjes (1996) and Eswaran et al. (1993) reported that around

1550 Pg (1.55 x 1015 Kg) of soil carbon can be found just in the upper one meter of the soil which is about three times and twice the amount of carbon stored in the above ground biomass and atmosphere respectively. At present, globally cultivated soils are reported to have lost around 50-70 percent of their original carbon content (Lal, 2010). This implies that there is a great opportunity to return carbon back into the soil where it can generate a positive response, making the soil healthy and be a solution to numerous problems including climate change, food, and water security.

Putting carbon in the soil can also be a solution for food security as carbon forms the basic necessity for retaining and enhancing soil fertility and productivity(Laird, 2008). Healthy soils have lots of pores structure between their aggregates, creating air pockets and allowing more water to be infiltrated into the soil profiles(Naveed et al., 2014). Presence of these pores space improves the soil drought resilience capacity as plants would be able to thrive even during dry spell(Bot and Benites, 2005). When these pores are missing, the soil is compacted, losing its ability to absorb water and ultimately results in flooding and erosion. For the soil to have higher porosity, the soil must have carbon in it to be able to build aggregates(Oades, 1988). Thus rebuilding and improving carbon in the soil can provides multiple benefits from reducing greenhouse gases in the atmosphere to improved crop yields and even to increased water retention capacity. Storing carbon in the soils is not only a possible solution but it is a win-win situation because unlike other methods, it involves no risk in the process.

Carbon is stored in soil both as organic and inorganic(Jobbágy and Jackson, 2000). Soil inorganic carbon (SIC), primarily calcium, is derived from weathering of parent materials or through the reaction of soil minerals with the atmospheric CO_2 (Lal, 2007). SIC is an important portion of the soil carbon reservoir, however, in the present study we consider only data of soil organic carbon (SOC), which is stored in the soil as soil organic matter. Organic carbon is formed in the soil when autotrophic organisms namely plant and microbes synthesize the atmospheric CO_2 and convert it into organic materials. Plants capture CO_2 from the atmosphere and use it in the process of photosynthesis. During this process,the photosynthetic cell containing chlorophyll converts the carbon from carbon dioxide into energy rich organic molecules (glucose, starch). The plants utilize some of these to produce above growth such as stem, leaves, etc. However, as much as 40 percent of these rich energy carbon molecules are being transferred to the soil through the plant's root and stored as belowground carbon (Dilkes et al., 2004). Soil also receives carbon inputs through the death of plants and animals which are being broken down into organic form by soil microorganism and are stored in the form of soil organic matter (SOM). The stored carbon in the form of SOM is known as soil organic carbon (SOC). If left undisturbed, these stored carbons in the soils in the form of SOM can remain for "an average life-time of hundreds to thousands of years" (Azeez, 2009).In the present work, SOC refers to the total organic carbon but not its fraction, but one should note that SOC can be fractionalized further into labile and non-labile carbon which includes particulate organic carbon, dissolved organic carbon, readily oxidizable organic carbon, etc. For further reading, it is good to note that from here on, SOC stands for total soil organic carbon, unless stated otherwise.

1.2 Purpose of the study

Despite the above stated facts, limited quantitative information from both field and modeling, on soil carbon especially in Northeastern(NE) region of India are available. NE region comprises of large numbers of flora and fauna which are the main source for soil carbon and is further supported by complementary factors, particularly high rainfall which enhances vegetation growth and hence the soil is believed to have very high carbon content. Therefore, there is a need for accurate SOC data information regarding how much and where carbon is stored, how much carbon is sequestered or lost over time, awareness information about the various factors that cause or can enhance SOC storage so that the people, government or policy makers can manage, harvest and protect the landscape of these regions for soil carbon storage to play a role in global climate change and to ensure food security.

1.3 Problem statement

This research work, therefore,consists of baseline investigation of soil carbon dynamics of a selected region of NE India, focusing on various sectors, namely, on developing a low cost and accurate method for mapping of SOC digitally, on evaluating the underlying mechanism and factors affecting SOC storage, on how carbon content of a region may change under the different climatic condition and on finding ways to improve the carbon content in the soil.

1.4 Research objectives

To evaluate the soil carbon dynamic based on field measurement and modeling that will contribute to the agriculture and global environment benefits. To accomplish this, the following objectives were defined:

- Prediction of soil organic carbon stock using digital mapping approach to evaluate the variables important in SOC prediction and to identify the potential regions for soil carbon sequestration.
- Evaluate the changes in soil carbon status and the underlying mechanism along the elevation gradients.
- Analysis of regional carbon fluxes from land-use conversion and landuse management.
- To develop an integrative tool in the form of a soil quality index to evaluate the effect of prevalent landuse and land management on SOC and soil quality as a whole.
- Assess the likelihood of changes in SOC content under different climatic scenarios.
- Investigate the effect of microbial enrichment on vermicompost in soil properties and carbon sequestration potential based on the results of the on-farm experiment.

1.5 Thesis outlines

The thesis report is built-up in chapters, each representing a specific topic.

- Chapter 2 presents a brief literature review of the work carried out previously related to the topic selected for the present study. The chapter discusses the role of climatic variables and other environmental factors in controlling the soil carbon storage; mapping of soil organic carbon; effect of landuse and land management on soil carbon; the importance of soil carbon related to soil quality; and on the role of compost and fertilizers on soil carbon.

- Chapter 3 described the detailed methodology used for prediction of soil organic carbon digitally. Digital soil mapping provides a means of regionalising soil carbon data from limited sample point to entire landscape by making use of soil formation factors as predictors. In order to predict SOC at the lower soil depth, the negative exponential function was used to describe the relation of SOC with depth.

- Chapter 4 evaluates the mechanism underlying the effect of altitude on SOC storage using path analysis approach.

- Chapter 5 presents the synthesis of land-atmosphere carbon fluxes as a result of landuse and land cover changes using multiple landuse data obtained from the National Remote Sensing Center (NRSC). Carbon fluxes as a result of forest and grassland management were also evaluated.

- Chapter 6 presents the methodology for defining an integrative tool in the form of soil quality index which can be used to evaluate the effect of landuse and management not just on soil carbon but on the soil quality as a whole. The overall soil quality index of different landuse was evaluated and compared.

- Chapter 7 described the methodology used for quantifying the amount of soil organic carbon (SOC) variation that could be explained by climatic variables alone. Then the joint behavior of SOC and climatic variables were also presented. This analysis is carried out to assess the likelihood of changes in SOC content under different climatic scenarios.

- Chapter 8 described the on-farm experiment conducted to investigate the effect of microbial enrichment on vermicompost for soil ecosystem services and crop productivity.

- Chapter 9 summarizes the discussion and conclusion of the entire research work and future scope of the research work

CHAPTER 2

Literature review

2.1 Introduction

Rapid increase of atmospheric CO_2 as a result of human activities have now brought attention and interest in knowing the earth's carbon stocks and its flow. Soil is recognized as one of the major storage of carbon and the soil's carbon storage capacity is much larger than the atmosphere and vegetation(Batjes, 1996). However, there is still an extensive open deliberation about the amount of soil carbon storage, the potential of various sites to store carbon and the role of many factors in controlling the storage and emission of soil carbon(Weissert et al., 2016). Therefore to manage, harvest and protect various landscape for carbon storage, it is important to understand the factors that influence it. Also with sampling and analysis being costly in nature, there is a need to develop low cost methods to quantify and estimate the spatial distribution of SOC(Minasny et al., 2006). There is a consensus that change in landuse and the results of various land management are the second anthropogenic source of carbon after fossil fuels burning(Swamp et al., 1999), therefore it is important to evaluate the role of various landuse and management on SOC storage.

Study on soil carbon is important not only for its role in global climate change but also in terms of soil fertility and crop productivity (Lal and Bruce, 1999). This research work, therefore, presents the evaluation of the factors that influence SOC formation and distribution; develop a cost effective method to quantify and monitor SOC; evaluate the impact of landuse changes and land management on carbon storage and identify the type of management practices that can help to promote carbon storage and soil quality. Hence, this chapter presents the work carried out previously related to the topic selected for the present study based on the following key points:

- Soil organic carbon and its various quantification methods.
- Factors controlling soil organic carbon.
- Digital mapping of SOC.
- Carbon fluxes from land-use conversion and management.
- Indicators of soil quality.
- Effect of compost and fertilizer applications on SOC and other soil properties.
- Conclusion of literature review.

2.2 Soil organic carbon and its various quantification methods

Soil organic carbon (SOC) refers to the amount of carbon stored in the soil(Lal and Bruce, 1999). It is one part of the largest carbon cycle, where carbon is being recycled through the vegetation, soil, ocean and atmosphere. Methods for measuring SOC can be broadly categorized into two categories: Direct methods and Indirect methods (Figure 2.1), and they are described as follows:

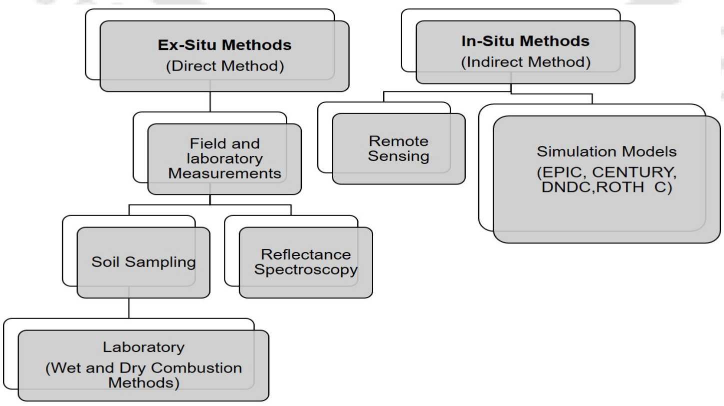


Figure 2.1: Methods for measuring soil organic carbon(Modified from Post et al. (2001))

2.2.1 Direct Method

Direct methods are time and cost consuming methods, as they require sample collection (as shown in Figure 2.2), sample preparation, chemicals and technology for analysis. However, they provide accurate results as compare to the indirect method. The steps involved in the direct method are discussed in the upcoming subsection.

Figure 2.2: Soil samples collection using core cutter (left) and soil samples preparation (right)

2.2.1.1 Analytical Measurement

In direct method,the soil samples collected from the field are analyzed for SOC content in the laboratory. The most popular laboratory methods that are used to calculate soil organic carbon are described below.

A)Walkley and Black Method

Walkley and Black method(Walkley and Black, 1934) is a rapid dichromate oxidation-reduction method. It works based on the following equations:

$$2Cr^2O_72^- + 3C^0 + 16H^+ = 4Cr^{3^-} + 3CO_2 + 8H_2O \tag{2.1}$$

$$Cr_2O_7^{2^-} + 6Fe62^+ + 14H^+ = 2Cr^{3^+} + 6Fe3^+ + 7H_2O \tag{2.2}$$

The amount of Cr^2O_7 reduced during the above reaction is presumed to be equal to the amount of organic carbon existing in the soil sample. Excess Cr^2O_7 left over is then titrated with standard ferrous ammonium sulfate solution to discover the volume of dichromate reduced during the reaction(Chatterjee et al., 2009). The soil carbon values were finally adjusted by a correction factor of 1.32 since this method failed to give complete oxidation of soil carbon. Many studies(Sutherland, 1998; Kamara et al., 2007) argue that this recovery factor is not sensible as soils arriving from diverse regions, different soil depths, with different mineralogy, are affected by different factors which will vary the recovery factor. However, Kamara et al. (2007) prove that the average value of the recovery factor in respective soil groups is not of much difference; thus it is possible to report the SOC value irrespective of soil types, depths, etc. using the same recovery factor. Another downside of this method is the production of hazardous chemicals after the reaction. However, despite these drawbacks, it is the most commonly used method because of its simplicity, low cost, minimum equipment requirement, and availability.

B) Loss on Ignition Method

Loss on ignition method(Sutherland, 1998) estimates carbon concentration based on differences in the mass of soil samples after its being ignited for a sustained period. The ranged of temperature employed in this method is from 300-550°C and the length of ignition period can be between 2 and 17 hours. This method assumes that organic carbon present in the soil is volatile at this temperature and duration. Thus, organic carbon is measured as the difference in mass of soil samples before and after heating. This method is very simple and relatively inexpensive compared to the Walkley and Black method. This method requires only an oven or muffle furnace that can reach a high temperature and a balance-equipment which is easily available. However, this method may overestimate the amount of organic C as combustion of soil components other than organic matter may lead to more weight losses. Carbonates present in the soils may also break down at these temperatures. Factors such as furnace types, duration, and the temperature of ignition may also influence the accuracy of this method.

C) Dry Combustion Method

Dry combustion method involved heating up a soil-catalyst mixture at 1000°C in a furnace in the presence of CO_2 free air or a stream of O_2 which is then followed by quantification of evolved CO_2 (Heanes, 1984). Automated C analyzer is the instrument which is widely used for dry combustion. The various automated steps involved in quantification of SOC by this method are: (i) conversion of Soil Carbon to CO_2 in a high-temperature chamber by oxidation; (ii) separation of CO_2 from the other gases; and (iii) quantification of CO_2 concentration by either mass spectrometry, thermal conductivity or infrared gas analyzing methods (Mikhailova et al., 2003). This method is accurate, quick and does not yield hazardous wastes. However, the instrument is very costly, and an increased level of training is required(Chatterjee et al., 2009).

D)Reflectance Spectroscopy

This method utilizes the concept of differences in absorption and reflection of light by the carbon content presents in the soil samples (McCarty et al., 2002). This method was designed for remote sensing but was modified for hand held on the ground. Before analysis, the instrument needs to be calibrated with known soil carbon values measured in the laboratory particularly those obtained from combustion method for better accuracy. This method is quick and non-destructive and can measure a large number of samples at a short period of time. However, the instrument is very costly, and an increased level of training is required. Also, the presence of moisture content may affect the amount of absorption and reflection of light. Hence, a prior measurement of soil moisture is required before taking any readings.

2.2.2 Indirect Method

Indirect methods which include remote sensing and model simulations are generally faster and can be carried out for a large scale. However, they are less accurate as compared to direct methods. Descriptions of some indirect methods are as follows:

2.2.2.1 Estimating SOC from Soil Reflectance through Remote Sensing

SOC can be estimated indirectly from soil reflectance based on the concept that there is a correlation between reflectance in certain spectral bands and SOC (Daniel et al., 2004; Ladoni et al., 2010) . Many researchers have attempted to estimate SOC from reflectance and come out with moderate to good results.

The soil predominantly has reflectance spectra in the region of 1100-2500 nm range, which comprise of three distinct absorption peaks about the 1400, 1900 and 2200 nm range and a small absorption peaks among the 2200 and 2500 nm (Chang, 2000). Increase in organic content of the soil will cause a decrease in soil reflectance(Shepherd and Walsh, 2002). However, with soil being a complicated material, a decrease in soil reflectance may be also due to the increase of some other soil properties(Nanni and Demattê, 2006). Therefore, many researchers have studied and indicated the portion of the spectrum that might be best acceptable for predicting SOC. Table 2.1 shows the reflectance source, spectral ranges and different methods carried out by different researchers across the world for predicting SOC. The reported R^2 in the middle infrared, near infrared and visible region was high.

2.3 Factors controlling soil organic carbon

Assessment of soil organic carbon storage and the factors influencing it would be important in research related to the global carbon cycle (Mao et al., 2015; Breulmann et al., 2016). In the past few years, a series of study has been conducted across the world under various climatic and landuse changes scenarios to evaluate the soil carbon occurrence and factors controlling its storage and distribution. The total amount of carbon deposited in the soil was reported to depends on numerous factors, viz. climate(Hobley and Wilson, 2016), topography(López-Vicente et al., 2009), vegetation (Yang et al., 2008), parent soil material(Dai and Huang, 2006) and even soil management(Luo et al., 2010).

A large body of literatures (Parton et al., 1987; Tian et al., 2000; Wang et al., 2014; Gray et al., 2015) reported that among these various factors, climatic variables account

Table 2.1: List of literature showing the prediction of soil organic carbon from remote sensing

Study area	**Reflectance source**	**Spectral Range (nm)**	**Methods**	**Authors**
Australia	Infra Analyzer 500 C	1100–2500	Multiple Regression	(Dalal and Henry, 1986)
U.S.A	Perstorp NIR Systems 6500	400–2498	Partial Least square Regression	(Chang, 2000)
Georgia	Aerial photograph	-	logarithm linear equation	(Chang, 2000)
U.S.A	Fourier transform spectrometer	1100–2300	Partial Least square Regression	(Reeves et al., 2001)
Greece	Ground-based sensor	350–2500	Multiple Regression	(Shepherd and Walsh, 2002)
Thailand	Stellar Net Spectro-radiometer	400–1190	Multiple Regression	(Daniel et al., 2004))
Australia	Varian Cary 500	700–2500	partial least-squares regression	(Rossel et al., 2006)
Brazil	Landsat TM	500-885	Multiple linear Regression	(Nanni and Dematte, 2006)
Germany	Hyperspectral image	350–2500	Partial Least square Regression	(Patzold et al., 2008)
Iran	LISS iii	520-1750	PCA, Soil line, simple Regression	(Ladoni et al., 2010)
India (Punjab)	ASD Field SpecPro spectro radiometer	460-2380	Partial least square regression	(Srivastava et al., 2015)

for most of the variation in SOC as they control the amount and quality of organic residues entering into the soil. Climatic variables have also been known to influence the microbial activity and several other geochemical processes inside the soil(Quideau et al., 2001; Hevia et al., 2003). On a global scale, temperature and precipitation are the two most important climatic variables reported to affect the SOC, and it is observed that SOC increases with increase in precipitation and decreases with increase in temperature(Follett et al., 2012; Herold et al., 2014). Temperature is reported to be negatively correlated with soil carbon, an increase in temperature will lead to increase in decomposition rate of SOC (Jobbágy and Jackson, 2000; Wang et al., 2014). Precipitation, on the other hand, tends to positively correlate with SOC, an increase in precipitation will increase plants productivity and leads to more inputs into the soils(Jobbágy and Jackson, 2000; Marín-Spiotta and Sharma, 2013). Despite these many studies, conclusion is still remained to be reached, with some studies reported that there is no effect of temperature on SOC(Giardina and Ryan, 2000; Thornley and Cannell, 2001). Likewise, precipitation was also reported to have no effect on SOC (Fröberg et al., 2008).

Disagreement also exists regarding the relative influence of climatic variables on SOC stock, with regional and local scale studies reporting that factors like vegetation types, landuse, soil types, soil management could explain most of the variation in SOC stock(West and Post, 2002a; Wiesmeier et al., 2014; Fang et al., 2015). Topographic factors were reported to have the greatest influence on soil organic carbon by influencing the redistribution of water and temperature(Shary and Pinskii, 2013; Longbottom et al., 2014). SOC content in the subsoil was reported to have a significant relationship with the soil textures rather than with climatic variables(Badgery et al., 2014; Mulder et al., 2015). Hobley and Wilson (2016) and Grimm et al. (2008) found that the factors controlling the SOC distribution vary with soil depth.Topography and landuse were reported to be the dominating factors in controlling SOC distribution on a hillslope and small scale studies(Swamp et al., 1999; Kaul et al., 2009; Wang et al., 2001; Wei et al., 2008). The amount of soil pH is also reported to have a great influence on the amount of organic carbon storage (Tavakkoli et al., 2015).

2.4 Digital mapping of Soil Organic Carbon

Being a key element of carbon fluxes between the atmosphere and terrestrial ecosystem, SOC has gained a lot of attention especially on its role of offsetting the amount of greenhouse gases(Ryan and Law, 2005). Besides this, SOC forms the basis of soil health, fertility and production(Lal and Bruce, 1999). Hence, global information on soil carbon storage is essential for environmental management and food security. However, it is practically impossible to sample and analyze soil sample for SOC at every location especially in difficult terrain areas.

In recent times, with the advancement in technology, there is a possibility of combining the new methods of science and technology with the traditional method of soil survey(Rossi et al., 2009). This has led to the development of Digital Soil Mapping (DSM), a concept which was formalized by McBratney et al. (2003). DSM can be defined as "the process of obtaining information about the spatial distribution of soil property by numerical models from field observation and knowledge of related environmental covariates(Minasny et al., 2006)". In his work (McBratney et al., 2003), he defined the concept of scorpan approach for predicting and mapping soil property which is formulated by the equation:

$$S = f(S, C, O, R, P, A, N) + \epsilon \tag{2.3}$$

Where,S = Soil property or prior knowledge of a particular soil property at a point

C = Climatic property at a point

O = Organisms, vegetation, fauna or any other human activities

R = Topography and other landscape attributes

P = Parent materials

A = Age or the time factor

N = Relative spatial position

ϵ = Spatial dependent residual

Since the introduction of digital soil mapping by McBratney et al. (2003), this technique have been successfully applied across the world to monitor and predict SOC at various scale. Polygon soil map generated using conventional methods are now being replaced with digital soil carbon map. These maps are stored and are being manipulated with the help of Geographical Information System (GIS), thus allowing for creating a large data for analysis as well as for easy interpretation(Mueller and Pierce, 2003; Triantafilis et al., 2009). Below we review some recent studies on digital soil mapping. We discuss the various methods used by them, such as linear model, random forest, neural network, regression tree, etc. for fitting the relationship between SOC and their environments and the various data employed for mapping of SOC.

Thompson and Kolka (2005) developed a soil-land scape model that can quantify the relationship between SOC and topographic variables in a watershed located in eastern Kentucky. A linear regression was used to generate the model. They reported that the topographic variables viz. aspect, slope, topographic wetness index, curvature could explained more than 71 % of the total SOC variation in their study area.

Bui et al. (2009) used piecewise linear decision tree model to predict the percentage of soil organic carbon in the agricultural land of Australia using climate variables, elevation, lithology, soil classes and moisture index as covariates. SOC was predicted up to a depth of 30cm with a resolution of 250 meters. The R^2 of the model used was 0.41. They noted that soil moisture is an important variable in predicting the SOC content. They also observed that the topsoil SOC content was highest in the high rainfall area and lowest in semi-arid and arid area.

Mishra et al. (2010) used geographically weighted regression (GWR) model to predict the amount of SOC in the mid-western United States. Climate variables, terrain attributes, bedrock geology, landuse data and normalized difference vegetation index were used as covariates. They reported that GWR improves the accuracy of prediction of SOC by 22% compared to multiple linear regression and by 2% over regression kriging.

Martin et al. (2010) used boosted regression tree model with vegetation types, climatic variables, soil properties, landuse and net primary product as covariates to predict and generates SOC map of 30cm in France. The R^2 of the model used was 0.91. Landuse was found to be the most important variables in predicting the SOC content. Along with landuse, the amount of clay content was also reported to be important in determining the amount of SOC stocks.

Adhikari et al. (2014) predict the spatial distribution of SOC at five different depth intervals 0-5, 5-15, 15-30, 30-60, and 60-100 cm for Denmark. For the analysis, soil map and DEM derivatives were used as predictors. Condition based regression rules were used to obtain relationship between SOC and its predictors. They reported that the most important variables in predicting the SOC varies with depth. These variables include precipitation, landuse, wet land, elevation and soil types.

Wiesmeier et al. (2014) used Random Forest model to predict the SOC for the state of Bavaria in Germany. They reported that the model showed a high prediction accuracy for the prediction of SOC stock of cropland, grassland and forest land, however the model failed to predict the SOC of high bogs areas. Controlling parameters for SOC storage were identified as landuse, soil moisture, soil types and precipitation.

Were et al. (2016) quantify and mapped the SOC stock up to 30cm in Eastern Mau Forest Reserve located in Kenya with the help of field data, remote sensing, geographical information system and statistical model. They reported that elevation, silt content and band 11 of Landsat 8 operational land imager together could explained more than 72 % of the total variation in SOC stock.

Yang et al. (2016) used soil depth function and random forest model to mapped SOC stock of northeast Tibetan Plateau up to 1 meter depth. They also predict the SOC content of mattic epidon which is reported to be a special soil surface rich in SOC content. Their model showed that vegetation-related variables as the most important variables. The influence of elevation was also reported in their model.

2.5 Carbon fluxes from land-use conversion and management

Since the industrial revolution, the amount of carbon dioxide in the atmosphere have increased rapidly(IPCC, 2007). Carbon is emitted into the atmosphere through various activities including the burning of fossil fuels, cement production, deforestation and landuse change(Houghton, 1999).Although the major source of carbon emission is the burning of fossils fuels, landuse and landcover(LULC) conversion and various land management are reportedly to account for approximately 33% of the increase in atmospheric carbon dioxide over the last 150 yrs(Houghton, 1999), 20 % between the period of 1980 and 1990(Hauglustaine et al., 2007) and approximately 12.5 % over 2000 (Friedlingstein et al., 2010). The declining in numbers is due to an increase in fossil fuels emission. As a result of this, the effect of landuse changes on the carbon balance within the terrestrial ecosystem has gained a lot of attention in the recent decades(Houghton, 2002; Leite et al., 2012).

Our terrestrial ecosystem is a potential carbon stock and if we managed it properly, it can play a major role in combating the excess anthropogenic carbon emission(Lal, 2004a). Changes in landuse affect the soil and vegetation of a terrestrial ecosystem and ultimately changes the amount of carbon held on that particular land(Houghton and Goodale, 2004). For instance changes in landuse type from high vegetation biomass (forest) to low vegetation biomass (agricultural land) will result in carbon emission (Lai et al., 2016). Such changes will not only affect the carbon stored on the plant's biomass but also will affect the amount of vegetation residues into the soil which is the main source of soil organic carbon(Post and Kwon, 2000). Landuse management such as control of man-made forest fire, control of plants diseases, control of pest, proper irrigation and proper usage of fertilizers in croplands, proper managements of grassland can affect the amount of carbon storage and carbon emission(Apps and Price, 2013). For example application of the right amount of fertilizers will help to promote plants growths and ultimately will lead to carbon accumulation, prevention of plants diseases will reduce carbon emission (Shevliakova et al., 2009). Thus knowing the source and sinks of carbon from landuse changes and land management is important in view of

reducing carbon emission and in fighting against climate change.
Several data sets, methods and model have been used to calculate the carbon flux from LULC and land management. Several studies have used bookkeeping model, processed model and even empirical model defined by IPCC to study the disturbance of carbon pool by human activities. Here we reviewed some of the recent studies related to changes in carbon fluxes as a consequence of landuse changes.

2.5.1 Bookkeeping model

Bookkeeping model track changes in areas of various uses and utilizes standard curves to estimate the changes in carbon pool.

Houghton (2003) used bookkeeping model to calculate net source and sink of carbon as a consequence of changes in landuse and of land management in nine regions of the world. For analysis, two types of data were used: rate of change of landuse and changes in carbon storage per hectare due to changes in landuse and land management. The data for rate of change in landuse were obtained from national handbooks and from forestry and agricultural statistics. Data for changes in carbon stock following landuse disturbance were obtained from various studies published in the literature. According to the results from the analysis, changes in landuse were responsible for a sink in carbon for some part of Europe and America and act as a source in other non-tropical regions.

Tang et al. (2012) analyzed the variation of soil carbon stock in relation to changes in landuse land cover in Zhenlai County situated in China. Analysis was carried out using bookkeeping model with the help of remote sensing data. They have also analyzed the effect of fertilizers management on SOC stock. Results of their study indicated that Zhenlai is a net source of CO_2 as a results of landuse conversion and fertilizers managements. SOC stocks was reported to decrease by 48% from the year 1980 up to the period of study.

Andersen et al. (2016) assessed the carbon emission resulting from landuse changes in Bolivia between the years 1990-2000 and 2000-2010 using bookkeeping model. For the analysis, they employ logistic carbon regeneration curve in their estimation for above ground biomass.

$$CAR_{v,a} = \frac{CAP_v}{1 + e^{\alpha_V - \beta_v a}} \tag{2.4}$$

Where, $CAR_{v,a}$ = above ground carbon contents during regrowth of forest type v of age a

CAP_v = carbon content for mature forest type v

α_V and β_v = parameters that define the shape of the logistic function

Results of their study indicated that the net CO_2 emissions as a result of landuse increases by approximately 65 million tons per year during 1990-2000 to 93 million tons per year during 2000-2010.

2.5.2 Process model

Apart from bookkeeping model, other researchers have also used processed model for estimation of carbon loss or again from landuse changes. These models calculate the carbon density in both soils and vegetation based on climate data and other factors as an input.

Shevliakova et al. (2009) built a dynamic land model (LM3V) to simulate the flow of CO_2, water and energy between land and the atmosphere as the outcomes of changes in landuse and land management namely changes in cropland, pastures, shifting cultivation. Here they analyzed the behavior of this model with inputs of observed precipitation data and four historic landuse data for the years 1700–2000. Their results showed that croplands are a carbon source of 0.6 to 0.9 Gt C/a whereas pastures vary from carbon source of 0.37 to a carbon sink of 0.15 Gt C/a.

Smith et al. (2008) combined the used of remote sensing data with process model to accurately estimates the changes in carbon fluxes in northern Europe (4-30°E, 55-70°N). The satellite data that was used in the study includes multi-spectral reflectance from vegetation sensor. By including satellite images they aimed to improve the accuracy of prediction of net primary production of the conifer forest predicted by the processed model. Their results predicted average 0.22 kg C m^{-2} yr^{-1} NPP for conifer forests which is comparable with forest-inventory-based estimates for Sweden.

2.5.3 Standard empirical models developed by IPCC

Apart from bookkeeping and process based model, IPCC also published standard procedure for calculating changes in soil and vegetation pool as a result of landuse changes and land management. As per this method, the IPCC has suggested two basic approaches to calculated changes in carbon stock ΔC. First approach is the gain-loss approach. Here ΔC is calculated as the difference between carbon gains (as a result of growth of trees) and carbon losses (due to human activities such as fuel wood harvestings, fire and other disturbances)

$$\Delta C = \Delta C_{Gain} - \Delta C_{Loss} \tag{2.5}$$

$$\begin{aligned} \text{Where,}\Delta C &= \text{carbon stock changes annually (t C / yr)} \\ \Delta C_{Gain} &= \text{annual gain in carbon stock (t C / yr)} \\ \Delta C_{Loss} &= \text{annual loss in carbon stock (t C / yr)} \end{aligned}$$

The other approach is Stock- difference approach. Here the changes in carbon stock ΔC is the difference in carbon stock between the two accounting periods.

$$\Delta C = \frac{C_{t2} - C_{t1}}{t_2 - t_1} \tag{2.6}$$

$$\begin{aligned} \text{Where,}C_{t2} &= \text{carbon stock in time } t_2 \\ C_{t1} &= \text{refers to carbon stock in time } t_1 \end{aligned}$$

Zhang and Cao (2015) analyzed how changes in landuse both at national and provincial level affect the carbon storage in China during the periods of 1980 to 1995.For the analysis they prepared three landuse maps of the years 1980, 1995 and 2010. They also obtained vegetation and soil carbon maps from National Geomatics Center of China. Empirical models defined by the IPCC were then used. Their results revealed that even though there is losses of carbon due to conversion of landuse, however, these losses were ultimately balanced by contrary conversions. This is due to effort made by their governments to improved various landuse particularly of forest covers. They even observed that the total carbon losses even reduced between the years 1995 to 2010.

Lai et al. (2016) analyzed changes in both soil and vegetation carbon stock in China resulting from both landuse changes and management between the years 1990 and 2010. For analysis, they used Tier 1 approach as defined by the IPCC. They have taken the values of carbon density of various vegetation from the published literatures and for forest management they used the data obtained from 5^{th} and 7^{th} National Forest Inventory. Their results demonstrate that changes in landuse have resulted in reduction of soil carbon by 11.5 Tg, however, the biomass carbon has increased by 13.2 TgC/year. Land management including forest fires and pest has resulted in large carbon loss of around 101.8 TgC/year.

2.6 Soil quality

Knowing that landuse and land management can greatly affect carbon emission, it is therefore important to understand how soils respond to different landuse and management scenarios in order to make a sound decision in the selection of suitable landuse and land management (Krishna et al., 2003). Also to evaluate the effectiveness of particular management or practices, single individual soil property like soil carbon may not be sufficient to come to a conclusion, hence a concept of soil quality index (SQI) by integrating various soil parameters could provide us a better result in interpreting the quality of a soil (Doran and Parkin, 1994). This section, therefore, review the concept of soil quality and some of the works related to soil quality.

In the recent decades, the concept of soil quality has gained a lot of attention and has come to be the forefront in environmental sustainability (Zibilske, 1998). The term soil quality, soil degradation, soil restoration, soil resilience are now being used more frequently, and with more urgency in a need to protect our global environment. Often, the important role of soil is overlook in comparison to water and air, as these two resources have a more clear association with human well being. However, soil quality has a direct effect on the quality of water and air and more importantly on human and animal health (Doran and Parkin, 1994). Soil being a vital resource, it should therefore be given the same level of care and protection as that of water and air.

While soil quality look to be a straight forward concept, however, it has been difficult to define and more hard to measure (Karlen et al., 1997). A proper definition of soil quality will find its application over a wide range of fields. The first definition of soil quality is related to agriculture. Few researchers (Karlen et al., 1992; Parr et al., 1992) have defined soil quality as the capability of soil to function as a medium for the development of plants needed to sustain human and animal life. While soils play a major role in agriculture, the role of soil in other environmental and recreation purposes also need to be considered. Soil acts as important medium for recycling of various nutrients and energy and also play a greater role in purification and decomposition of various waste and hazardous materials (Huinink, 1998). Doran and Parkin (1994) defined soil quality as:
'The ability of a soil to operate within the ecosystem boundaries so as to maintain the biological productivity, keeps up the environmental quality and improves plant and animal health'.

Likewise, soil quality has also been defined as the balance between soil degradation and soil resilience (Lal, 1998). Soil degradation can be defined as the short to medium condition where one or more potential function of a soil are being deteriorated due to improper land management, change in landuse and other processes that promotes loss of soil function (Lal, 1997). Whereas soil resilience is the ability of a soil to return to its initial condition after being disturbed (Lal, 1998). Thus soil quality can be defined in numerous ways, but it should be flexible enough to account for all the function that a soil can perform.

2.6.1 Minimum Data Set Concept

Due to financial constraints related with the cost of soil sampling and analysis, the number of soil quality indicators that are actually required to be analysed on a given set of soil samples to determine their quality are lessened to minimum number of data sets. This selection of minimum key indicators are carried out based on expert opinion (Doran and Parkin, 1996) or using statistical data reduction technique or a combination of both.

For instance, Schipper and Sparling (2000) carried out an analysis for 16 soil quality indicators out of a set of soil samples collected from 29 locations in New Zealand. They then used principal component analysis (PCA) a statistical methods to detect the few most influence indicators that are critical in separation of soil samples taken from four different landuse (forest, grassland , arable and plantation). From PCA they obtained six subset of indicators that represents all the physical, chemical and biological properties of a soil, and these six indicators could separate the soil samples into different landuse similar to that of using the complete 16 set of indicators. In their subsequent study, carried on 222 soils sample in New Zealand (Sparling and Schipper, 2002), PCA could identify four principals components which represents the physical properties, chemical properties, organic matter related properties and water characteristics properties.

Andrews and Carroll (2001) in their case study demonstrate clearly on how to select minimum data set from a larger dataset. First using multivariate statistics, they select the indicators which accounts for more than 85% of the variation. Subsequently they used principal component analysis (PCA). From PCA results, the principal components (PCs) that explained more than 5 % of the variation were examined properly. Finally the PCs with highest weight were selected.

Kairis et al. (2014) in their study presents another way to reduce the number of indicators. They used multiple regression to determine the most important indicators, and the data sets are further reduced by removing the highly correlated indicators.

WestA (2010) presents a participatory approach of selecting minimum data sets, in which various experts were ask to give their view on the most important indicators and rank them based on their sensitivity to various soil functions.

We summarized in Table 2.2 few of the most conceptual publications on soil quality indicators all over the world. Studies dealing with only biological indicators neglecting physical and chemical indicators and vice versa were not included in this compilation.

Table 2.2: Publications on soil quality indicators

Regions	References
Asia	(Cunxu and Xiaoyong, 1991) (Lin-zhang and Yan-hong, 2001)(Shi-rong and Jian-guo, 2009) (Yu-Dong et al., 2013) (Chauhan and Mittu, 2015)
Europe	(Torstensson et al., 1998) (Huber et al., 2001) (Loveland et al., 2002) (Bone et al., 2010) (Armenise et al., 2013)
USA and Canada	(Larson and Pierce, 1991) (Doran and Parkin, 1994) (Andrews and Carroll, 2001) (Shukla et al., 2006) (Wienhold et al., 2009)
New Zealand and Australia	(Schipper and Sparling, 2000) (Southorn and Cattle, 2000) (Sparling and Schipper, 2002) (Cotching and Kidd, 2010)
South America	(Velásquez et al., 2007) (Lima et al., 2013)

Similarly study dealings with soils of a particular landuse only were not included.

A more advanced approach to evaluate the soil quality is with the help of standard scoring functions which normally have the shapes of i) more is better ii) optimum range and iii) less is better. The shape of such curve is derived from values obtained from the past literatures and with the help of expert opinions (Doran and Parkin, 1996). Here each soil indicators are being transformed into a value ranges from 0 to 1 (Rashidi et al., 2010), with 0 represent the poorest values and 1 represents the best value. Here the baseline values is generally chosen as the midpoint between the threshold values (Doran and Parkin, 1994).

Glover et al. (2000) adopted this approach to evaluate the soil quality in a conventional, organic and integrated apple production system. The reported that soil quality was found to be higher in integrated production system compared to conventional and organic system.

Melo Filho et al. (2007) used this approach to evaluate the soil quality of natural forest soils in Brazil. They observed a poor soil quality index of 0.4620, the reasons because the soil of these forest are subjected to crop production.

2.6.2 Commonly proposed soil quality indicators

We summarized the most commonly proposed soil quality indicators as per the results from referred publications in Table 2.2. Although this may not represents all the publications related to soil quality, however, we noted by increasing the numbers of evaluated publications from 15 to 21, we obtained a more or less the same outcomes. As per these data, we observed that soil organic carbon and pH as the most commonly proposed soil indicators (Figure 2.3) followed by texture, available phosphorous, cation exchange capacity and electrical conductivity. Recent publications even reported earthworm as a nutrients and water cycling indicators.

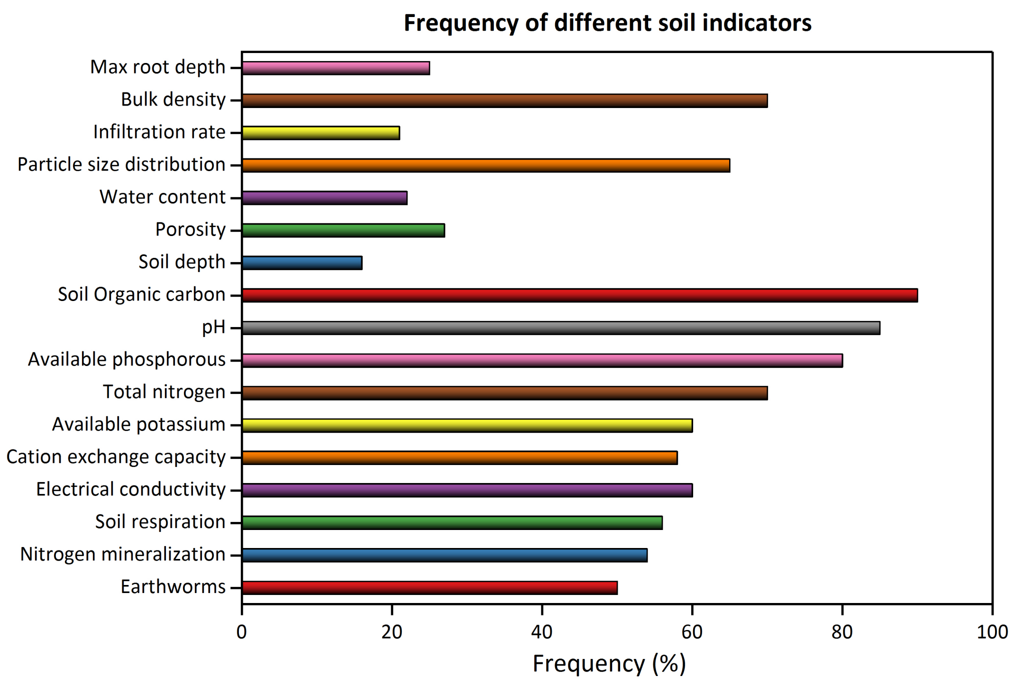


Figure 2.3: Frequency of different soil indicators as per the results from the evaluated publications (n=21)

2.7 Effect of compost and fertilizer applications on SOC and other soil properties

The amount of SOC content in the soil plays a critical role in maintaining the soil quality and crop productivity(Larson and Pierce, 1991). Presence of low concentration of SOC (less than 1% by weight) have been reported to have a deleterious effect on crop productivity (Guo and Gifford, 2002). Depending on the amount and the nature of the applied fertilizers (organic or inorganic), SOC and other soil properties have been reported to be modified under different soil and climatic conditions (Lal, 2004b; Davis et al., 2006) . Keeping in view the importance of SOC, here we reviewed the pertinent literatures where application of various compost and fertilizers have been stated to modify the crop productivity and soil properties particularly, SOC.

Increase in the concentration of SOC from 1 to 4 t C ha^{-1} and increased in formation of slaking-resistant macro aggregates have been reported following the application of organic manure (Aoyama et al., 1999; Mikha and Rice, 2004) . From a case study in UK, Powlson et al. (2012) reported a mean annual increase in SOC content of a topsoil of approximately 60 Kg C ha^{-1} yr^{-1} , 50 Kg C ha^{-1} yr^{-1}, 180 Kg C ha^{-1} yr^{-1} and 60 Kg C ha^{-1} yr^{-1} following application of farm manures, cereal straw, digested bio solids and green compost.

Prasad and Singh (1980) in their study conducted in India reported that constant application of farm yard manure (FYM) and nitrogen phosphorous and potassium (NPK) fertilizers for 20 years help in keeping up and enhancing the soil physical properties and SOC content of the soil. However, the use of nitrogen fertilizers alone were found to somewhat deteriorated the soil physical properties.

Singh et al. (2007)conducted an experiment on a loamy soil of Punjab to investigate the effect of various treatments comprises of farmyard manure (FYM), wheat straw(WS), combination of wheat straw and rice straw (WS+RS) on the soil physical and hydraulic properties. At the end of experiment (1988-2001), they reported that organic carbon increases by 0.51%, 0.56% and 0.59% in FYM, RS and WS+RS respectively as compared to control. Improved in SOC was in turn reported to improve the soil aggregation status which improved the soil infiltration rate.

Katkar et al. (2012) conducted an experiment in central India to evaluate the effect of chemical fertilizers and manure application on the soil properties and yield of wheat and sorghum cropping system. The treatments includes 37.5 kg/ha of sulphur with recommended dose of NPK fertilizers, farmyard manure at 10 t/ha, 100% NPK, 2.5 kg/ha of zinc with recommended dose of NPK fertilizers. Highest soil quality were found in nutrients management with 100% NPK and farm yard manure.

Moharana et al. (2012) studied the long term effect of nutrients management on the soil quality and various pools of SOC viz. total organic carbon (TOC), labile organic carbon (LBC) and microbial biomass carbon (MBC). Following application of NPK and NPK+ FYM, significant improvement of soil fertility in terms of Olsen-P, NH_4OAc-K and $KMnO_4$-N were observed. Highest values of LBC (1.36 gkg^{-1}) were observed in NPK+ FYM, whereas highest values of WBC (7.86 gkg^{-1}) and TOC (11.48 g kg^{-1}) were found in plot with FYM treatment alone.

Gathala et al. (2017) carried out an experiment for two years in Modipuram, India in rice-wheat cropping system with different combination of tillage and crop establishment methods. They reported that when they avoid puddling and dry tillage and instead opt for brown manuring, zero tillage and residue retentions, an improvement in soil structural stability, soil infiltration and soil organic carbon was noted in the 0-15 cm soil layer.

Singh and Benbi (2018) investigated the impact of balanced Nitrogen (N), phosphorus(P) and potassium (K) and unbalanced N, NP,PK and NK with farm yard manure (FYM) on total organic and liable pool of carbon. They reported that around 72% of total organic carbon was found to be stabilized under balanced NPK+ FYM as compared to unbalanced N+FYM. This indicates that balanced NPK along with FYM favorably improved the organic matter composition.

Table 2.3: Effect of soil fertility management on SOC concentration in long term manuring experiment in India (Swarup, 1998)

Location	**Initial (g/kg)**	**Control (g/kg)**	**NPK (g/kg)**	**NPK + FYM (g/kg)**	**Period (yrs)**	**Rate of change over control (kgC/ha/y)**
Bangalore	4.5	4.8	5.9	8.4	10	101
Barrackpur	7.0	4.1	5.0	5.4	24	15
Bhubaneswar	2.6	3.7	5.7	8.1	21	59
Coimbatore	3.0	4.3	4.9	6.2	23	23
Delhi	4.3	4.4	5.5	6.7	25	25
Hyderabad	5.0	4.6	5.3	8.0	23	41
Jabalpur	5.8	5.3	6.0	9.8	25	48
Ludhiana	2.0	2.5	3.3	3.8	25	15
Palampur	7.8	7.3	10.0	12.0	22	60
Pantnagar	13.0	5.0	8.3	15.0	24	117
Ranchi	4.5	3.0	3.5	4.8	23	22

Various soil fertility managements on SOC concentration in long term application of NPK alone and NPK in combination with farmyard manure has been experimented in India. Table 2.3 showed the review of some of those studies as review by Swarup (1998).

Despite farm yard manure, vermicompost have also recently attracted farmers and researchers because of its capability of producing tremendous farm yield along with proper utilization of farm residue(Banik and Sharma, 2009). Vermicompost can be defined as a method of converting organic waste such as vegetable, farm residues, food waste etc. into nutrients rich fertilizers using the help of various worms (Lazcano and Domínguez, 2011). Biofertilizer are another substance that are expected to reduce the use of synthetic minerals and fertilizers (Wu et al., 2005). Biofertilizer contains living organisms derived from roots and cultivated soils which when applied help to restore the soil's nutrients and build soil organic carbon (Vessey, 2003).

Gopinathan and Prakash (2014) carried out an experiment in Tamil Nadu, India to evaluate the effect of vermicompost enriched with biofertilizers on the growth and yield of tomato plants as compared to chemical fertilizers applications. They reported that the application of vermicompost enriched with biofertilizers improves the overall height of the plants (cm), number of branches, number of leaves, length of the plants root and the overall crop productivity as a whole.

Shirkhani and Nasrolahzadeh (2016) conducted an experiment in Iran to evaluate the effect of application of vermicompost along with Azotobacter as a biofertilizer and chemical fertilizers on the yield and some traits of maize leaves under deficit and normal irrigation conditions. They reported that both the yield of maize as well as the leaves traits such as leaf area index, normalized vegetation index were found to decline under deficit irrigation condition. However, application of 6 ton/ha of vermicompost enriched with Azotobacter improves both the yield and leaves traits under both normal as well as in deficit conditions.

Mondal et al. (2017) conducted an experiment in West Bengal, India to study the effect of reduced dosage of chemical fertilizers mix along with vermicompost and biofertilizer on biophysical and chemical qualities of mustard. Six different reduced dosages of chemical fertilizers along with vermicompost and biofertilizer were evaluated. Performance of the crops were evaluated based on leaf area index, growth rate index, photosynthetic rate and harvest index. They reported that the use of 25 % of chemical fertilizers along with vermicompost is the most suitable for improving all their study attributes.

2.8 Conclusion and research gap

From the literature review on the various topics related to soil carbon, following conclusions have been drawn:

- Factors controlling SOC variation differs at different spatial scale: On a global scale, temperature and precipitation have been identified as the main factors controlling the distribution of SOC stocks, Whereas at the regional and local scale, topography variables were reported that have a greater effect on SOC distribution. The factors affecting SOC also vary with soil depth and thus should be assessed separately for different depth along the soil profile.

- Human cause of landuse change has resulted in carbon fluxes. Across the globe, several large scale studies have been carried to study the impact of landuse on carbon emission using a different approach and these studies often focused only on a specified landuse type. However, there is a significant knowledge gap exists surrounding the effect of landuse on carbon emission on a regional scale. Regional studies on the relationship between SOC, and landuse change focusing on all types of landuse are needed. Rapid changes in landuse in recent decades make the study a priority.

- Digital soil mapping has been widely used as a cost saving and accurate method for mapping and monitoring SOC stock.Researchers across the globe have successfully map SOC digitally using different data sets and different methods.

- Despite the advancement and importance of soil quality, study on soil quality especially related to evaluating the effect of various landuse and soil management systems in Northeast India are rather very meagre and scanty.

- This review found that application of compost and manure can result in greater carbon sequestration than equivalent amount of organic fertilizers and the effect of compost and manure on soil C lasts longer.

- The effect of changing climate on SOC is still a subject of continuing debate. With global warming and its likely effect on climatic variables, study of how SOC will respond to these changes and understanding the role of various factors affecting SOC storage is necessary for global environmental management and food security.

CHAPTER 3

Digital Mapping of Soil Organic Carbon

3.1 Introduction

Effective soil carbon management requires knowledge of the spatial distribution of soil organic carbon (SOC) and the factors that influence it. Usually, such spatial distribution information is represented in soil map made of polygons, where the soil properties within each polygon is considered to be homogeneous and the boundaries of polygon denotes abrupt changes in soil properties (Heuvelink and Webster, 2001). However, soil properties like soil carbon, which varies continuously in space, can be better represented with a continuous model. But it is practically impossible to sample and analyse soil samples for SOC at every location, especially in difficult terrain areas. With the advancement in technology as well as the ability to obtain secondary data like digital elevation model and satellite images, it provides us a quantitative approach to produce a continuous surface of soil properties like soil carbon. Such predictive model, known as digital soil mapping (DSM) (McBratney et al., 2003), provides a means of regionalising soil properties such as SOC from limited sample point to entire landscape, by making use of soil formation factors as predictors. These factors includes topographic variables, climate variables, parent materials, landuse, etc.

Most of the studies related to DSM (Kempen et al., 2011; Minasny et al., 2013) have dealt only with the estimation of SOC at the surface or at a particular depth. However, knowledge of SOC distribution at a lower depth is equally important when dealing with SOC storage (Hobley and Wilson, 2016). Although, SOC content is generally higher at the surface (Rumpel et al., 2002), however, it is more stable at the lower soil depth (Rumpel and Kögel-Knabner, 2011). Therefore, proper attention must also be given to soil at lower depth as it has the potential of retaining SOC for a longer duration. Recent studies (Yang et al., 2016) have shown that a combination of soil depth function with DSM is useful in estimating the continuous distribution of SOC at various depth.

As mountain environments are believed to be most vulnerable to climate change and NE India being mostly a mountainous territory, it is important to understand how SOC is stored and what are the factors controlling it in such kind of environments, in order to be able to provide feedback of SOC to global environmental changes. Hence, the first task attempted in this work is to generate continuous spatially explicit SOC distribution map across the NE region and to evaluate the factors controlling its distribution using a combination of the negative exponential function and DSM approach.

3.2 Materials and Methods

The method employed is based on the conceptual model "SCORPAN" as defined by McBratney et al. (2003). SCORPAN represents a list of soil forming factors as described in section 2.4. The aims is to predict and produce SOC map at the soil surface as well as at the lower soil depth. Therefore, the analysis was first carried out to construct a soil depth function describing the vertical distribution of SOC.Secondly, the predictive model was derived to map the soil depth function over the entire study area. This section will describe stepwise the analysis that was carried out as outlined in Figure 3.1

Step 1: Choosing the study area

The study area comprises of four states in Northeast India viz. Assam (26.2006°N, 92.9376°E), Meghalaya (25.4670°N, 91.3662°E), Nagaland (26.1584°N, 94.5624°E) and Tripura (23.9408°N, 91.9882°E) as shown in Figure 3.2. NE region has a subtropical climate and it is the rainiest region in India, with many places receiving an average rainfall of about 4000mm (Dikshit and Dikshit, 2014).

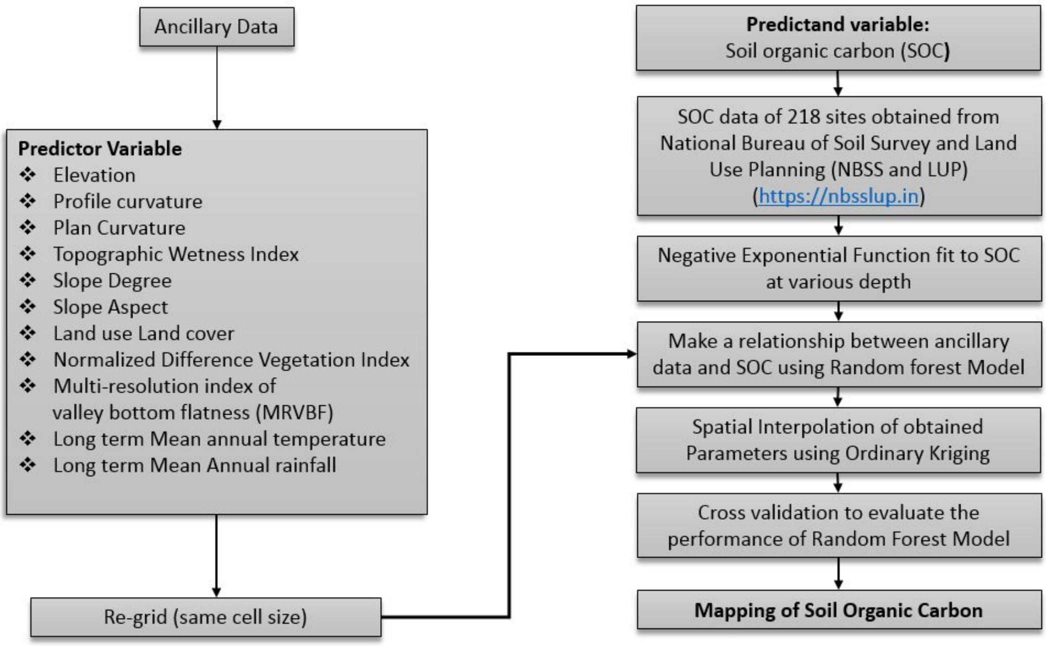


Figure 3.1: The methodological framework of the analysis

Step 2: Compilation of soil organic carbon data

We extracted secondary available published data from National Bureau of Soil Survey and LandUse Planning (NBSS and LUP) (https://nbsslup.in) (Bhattacharyya, 2004; Maji, 2004; Vadivelu et al., 2004; Singh and Bengtsson, 2005). Here, we used 218 sites which include information on soil carbon concentration (%) across different soil layers down to the parent material. Information on bulk density is required to convert SOC concentration (%) to volume based stock. Since information on bulk density was not available, we used a pedo-transfer function defined by Yang et al. (2016) to estimate the bulk density of each soil profile.

$$\text{Bulk density(BD)} = 1.47 - 0.09 \times \sqrt{SOC}\ (R^2 = 0.77, p = 0.001) \tag{3.1}$$

The soil carbon stock is then calculated as defined by Tang et al. (2017)

$$SOC(kg/m^3) = SOC(kg/kg) \times BD(kg/m^3) \tag{3.2}$$

$$SOC(tC/ha) = SOC(\%) \times BD(g/cm^3) \times \text{depth of soil}(cm) \tag{3.3}$$

$$SOC(kg/m^2) = SOC(tC/ha) \times 0.1 \tag{3.4}$$

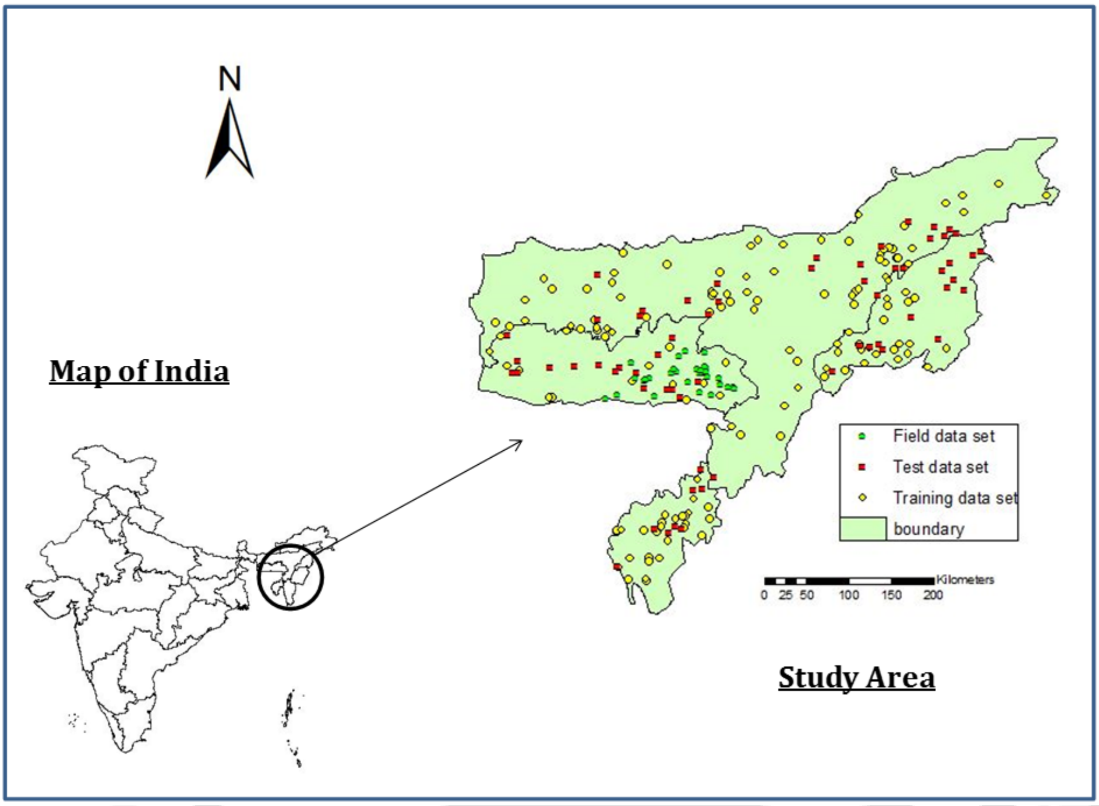


Figure 3.2: Study area: Assam, Meghalaya, Nagaland and Tripura

Additionally, 34 soil samples were collected from Meghalaya during June and July of 2016, which were used for independent model validation. The samples were collected based on different landuse. At each landuse, samples at different elevation and slopes (down slope, hill top) were collected. This allows us to take into account the effect of landuse and topography on SOC. The coordinates of each location were obtained with the help of global positioning system (Figure 3.2). Core cutter method was used to calculate the bulk density of the soil.

Laboratory work

All samples were then air-dried, sieved through 2 mm sieves, and stored for further analysis The soil samples were analyzed in the laboratory for SOC estimation using Walkley and Black rapid titration method (Walkley and Black, 1934). In order to determine the organic carbon present in the soil sample, a certain quantity of soil is digested in the presence of sulphuric acid and chromic acid. This oxidize the organic matter present in the soil sample.

Here 1g of the soil sample is digested with 10ml of 1N of $K_2Cr_2O_7$ and 20ml of concentrated H_2SO_4. The mixtures was shake thoroughly and allowed to react for 30 minutes. The mixture is then diluted with 20ml of water, 10ml of phosphoric acid and 1ml of indicator. The chromic acid left unreduced during the reaction is assumed to be the amount of carbon content present in the soil samples. This is determined by titration with standard ferrous ammonium sulphate (FAS) solution.

Here, weight of the sample =1 gram, normality of $K_2Cr_2O_7$ used = 1N, volume of $K_2Cr_2O_7$ = 10ml and normality of FAS =0.5 N

Here, 1 Litre of $K_2Cr_2O_7$ is equivalent to 12/4 g of carbon.

Or 1ml of $K_2Cr_2O_7$ = 12/4 ×1/1000 g carbon =0.003g carbon

(Where 12 is the atomic weight of carbon and 4 is the valency of carbon. Therefor 12/4 is the equivalent weight of carbon)

Therefore, Organic carbon (%)

$$= \frac{0.003 \times 10(\text{blank reading-Titration reading })}{\text{Blank reading} \times \text{wt of soil (g)}} \times 100 \tag{3.5}$$

Figure 3.3: Air dried soil samples stored in plastic bag

Step 3: Pre-processing of Environmental Parameters

For digital mapping of soil organic carbon, environmental parameters viz. climate variables, topography, landuse, vegetation and spatial positions were selected from the SCORPAN factor as defined by McBratney et al. (2003). All these parameters were resampled to a common grid of same resolution (90m).

Landuse

Landuse map was obtained from Bhuvan portal (bhuvan.nrsc.gov.in/map) in digital format on request. This landuse map was then projected into UTM zone 46N. As per the obtained LULC map, majority of the areas in NE India are of forest and agricultural areas, hence the LULC map was reclassified into three major classes, viz. forest area, crop land and other landuse.

Terrain Attributes

Digital elevation model of 90 meter resolution was obtained from Shuttle Radar Topography Mission Terrain (SRTM). All primary and secondary terrain attributes were prepared using ArcMap 9.3 (http://www.esri.com) and SAGA GIS software (www.saga-gis.org). Definition and units of all the terrain attributes used in this study are shown in Table 3.1

Table 3.1: Terrain attributes along with their definitions

Terrain Parameters	**Definition**	**Units**
Elevation	Height above sea level	Meter
Aspect	Direction of steepest slope	Degrees
Slope	Rate of change of elevation in the steepest direction	Percent
Profile curvature	Rate of change of slope down a slope line	Degrees per 100 meter
Plan curvature	Rate of change of aspect along a contour	Degrees per 100 meter
Topographic Wetness Index	Measure of topographic control on soil wetness	none
Multi-resolution index of valley bottom flatness	Determine flatness and lowness of a valley	none

Climate data

Climate data, 0.25°× 0.25°resolution average mean annual precipitation and 1°× 1°resolution average mean annual temperature for a period of 30 years (1976 -2005) were obtained from India Meteorological Department (IMD), Pune.

Vegetation data

Normalized difference vegetation index (NDVI) data which represents the amount of vegetation, were extracted from MODIS website as per the dates of SOC data (modis.gsfc.nasa.gov). It is obtained by measuring the difference in values between the near infrared band (where vegetation strongly reflects) and the red band (where vegetation strongly absorb.

$$NDVI = \frac{(NIR - RED)}{NIR + RED} \tag{3.6}$$

NDVI values ranges from -1 to +1. When a NDVI values is closes to +1, it indicates a dense vegetation cover. On the other hand, if its value is negative it denotes that its water. .

Step 4: Modelling distribution of SOC with depth

Many studies (Mishra et al., 2009; Scharlemann et al., 2014; Yang et al., 2016) have used mathematical functions such as exponential, logarithmic, power and quadratic to study the relation between SOC distribution and depth interval. However, in this study, since the data extracted from NBSS and LUP are of different depth increment, we used a negative exponential function (Equation 3.7) to describe the relation of SOC with depth, so that we can compare SOC at different soil depth interval.

$$SOC(kgC/m^3) = (SOC_a – SOC_b)\exp(-kd) + SOC_b \tag{3.7}$$

$$SOC_a, SOC_b, k \geqslant 0 \tag{3.8}$$

Where SOC (kg C/m^3) refers to soil carbon stock as a function of depth, SOC$_a$ is the soil organic carbon stock at the soil surface, SOC$_b$ is the soil organic carbon stock at the lowest soil depth (in this case up to the parent materials), k refers to the decay constant (meter^{-1}) and d is the depth interval in meter.

Equation 3.7 is fitted to individual soil profile using nonlinear least square regression to obtain value of k. Once we obtain the value of k, we substitute its value in Equation

3.7 to evaluate the prediction accuracy of the negative exponential function. This is carried out by calculating the differences between fitted and observed SOC (kgC/m^3) of each location at different depth interval up to the parent materials.

Step 5: Model a relationship between the parameters of exponential depth function and the environmental covariates using Random Forest

To model a relationship between the parameters of exponential depth function and the environmental covariates, classification and regression method in Random forest (RF) was used. The analysis was performed using Random Forest package in the statistical software R (Liaw and Wiener, 2002). RF is a family of ensemble machine learning methods which predict a response variable given a set of predictors by aggregating the outcome of multiple decision trees. Each of these trees is uniquely constructed using bootstrap of training data sets (Schapire et al., 1998). Bootstrap sampling help in creating randomness of the training data which help in removing correlation of variables and improve the accuracy of each tree (Gislason et al., 2006). Additionally, RF provides the importance ranking of each variable used in the model. This is computed as a function of how much prediction error increases if a particular input variable is permuted while all the other variables remain unchanged. RF has several advantages over other modeling methods, where it can operate with large number of trees to produce low bias and low variations results. It can also work on both numerical and categorical data sets.

For model building, RF depends on three parameters, number of tree (N_{tree}); minimum number of points data to be included at each terminal node size (N_{size}) and number of features at each try (M_{try}).The default number of N_{tree} =500; here we used N_{tree} =1000 as more number of trees result in a more stable result (Breiman, 2001).An iterative approach was used to determine the M_{try} by minimizing the out of bag mean square error (MSE_{OOB}) as defined by Equation 3.9. For N_{size} we used a default value ($N_{size} = 5$)

$$MSE_{OOB} = \sum_{i=1}^{n} \frac{1}{n} [Y_i - Y_i^{OOB}]^2 \tag{3.9}$$

The output obtained from spatial prediction carried using RF model was subjected to validation. Root mean square error (RMSE) and mean error (ME) were used to evaluate the performance of the model.

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}[\bar{P} - O_i] \tag{3.10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[\bar{P} - O_i]^2} \tag{3.11}$$

Where $\bar{P}, O_i$ refers to predicted and observed SOC stock and n refers to the number of observations.

Step 6: Test for spatial autocorrelation of parameters of exponential function

The parameters of exponential function (SOC_a, SOC_b, k) obtained from a random forest model are then analyzed for presence of spatial autocorrelation using Moran's Index (I) (Moran, 1950). This index measured the spatial autocorrelation of the variables i.e. how the variables are related based on their measured values and locations. If the value of this index is greater than 0, it indicates a positive spatial correlation among the measured variables; value of the index less than 0 means a negative spatial autocorrelation while a value of 0 means perfect randomness (Tang et al., 2017).

$$I = \frac{N\sum_{i=1}^{n}\sum_{i=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{(\sum_{i=1}^{n}\sum_{i=1}^{n} W_{ij})(\sum_{i=1}^{n}(X_i - \bar{X})^2)} \tag{3.12}$$

Where, N = the total number of spatial units indexed by i and j

X_i = variables of interest

$\bar{X}$ = the mean ofX_i

W_{ij} = spatial weight of the matrix with zeroes on the diagonal

Result of this test, led to the use of interpolation method (Ordinary kriging) which work on the basis of spatial autocorrelation to interpolate the predicted parameters (SOC_a, SOC_b, k) across the study area.

Step 7: Interpolation of parameters of the exponential function over the entire study area using Ordinary Kriging

Kriging is one of the geostatistical interpolation methods used to estimate value of unknown random variable Z base on the scattered sampled data set through semivariogram analysis(Miller et al., 1988; Lark, 2002) . An estimate value at unsampled point is a linear weighted average of n observation surrounding the unsampled point. It is calculated as:

$$Z(S_0) = \sum_{i=1}^{n} \lambda_i z(S_i) \tag{3.13}$$

Where λ are weight assigned to each observed data points. Detailed of ordinary kriging was given by Webster and Oliver (2007)

Step 8: Prediction of SOC stock over the entire study

The interpolated parameters of exponential function along with raster map of a defined depth interval were then incorporated into equation 3 to produce SOC map of the study area at various depth. Two maps 0-30cm and 0-50cm were produced in this study. SOC map of different depths can be produced by varying the depth parameter in Equation 3.7.

Step 9 Model validation

The model was then validated with the test data set that was partitioned from the original data set and with 34 data collected from field sampling up to 15cm depth

3.3 Results

3.3.1 Statistical Parameters of SOC at the soil surface

Descriptive statistics of SOC contents at soil surface for the soil data extracted from NBSS and LUP and those obtained from field sampling are shown in Table 3.2. The depth increment of the soil samples extracted from NBSS and LUP varies with location, with a mean depth of 15 cm and average SOC stock of 3.42 kg/m ^{2}. Soil data collected from field sampling up to 15 cm depth for independent validation analysis (refer as field data in Table 3.2) has an average SOC stock of 5.33 kg/m^2.

3.3.2 Exponential Depth Function

Based on R^2 values of fit and visual interpretation of plot between fitted and observed data (Figure 3.4), exponential fitting of SOC to soil depth using Equation 3.7 was found

Table 3.2: Statistical Parameters of SOC at the soil surface

	Mean	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
SOC Content (kg/m^2)	3.42	2.84	2.14	0.57	12.22
Depth (cm)	15.88	15	4.44	5	31
Field data (kg/^{2})	5.33	5.60	1.85	0.26	7.53

to fits the data adequately. Out of 218 soil profiles, 100 soil samples had an R^2>0.96, 148 soil samples had R^2>0.9, 198 soil samples had R^2>0.8, 205 samples had an R^2>0.7, while 13 soil samples had a poor fit with R^2<0.7. Thus exquisite results obtained from this study, signify that a simple three parameters negative exponential function can be used to adequately model the distribution of SOC with depth.

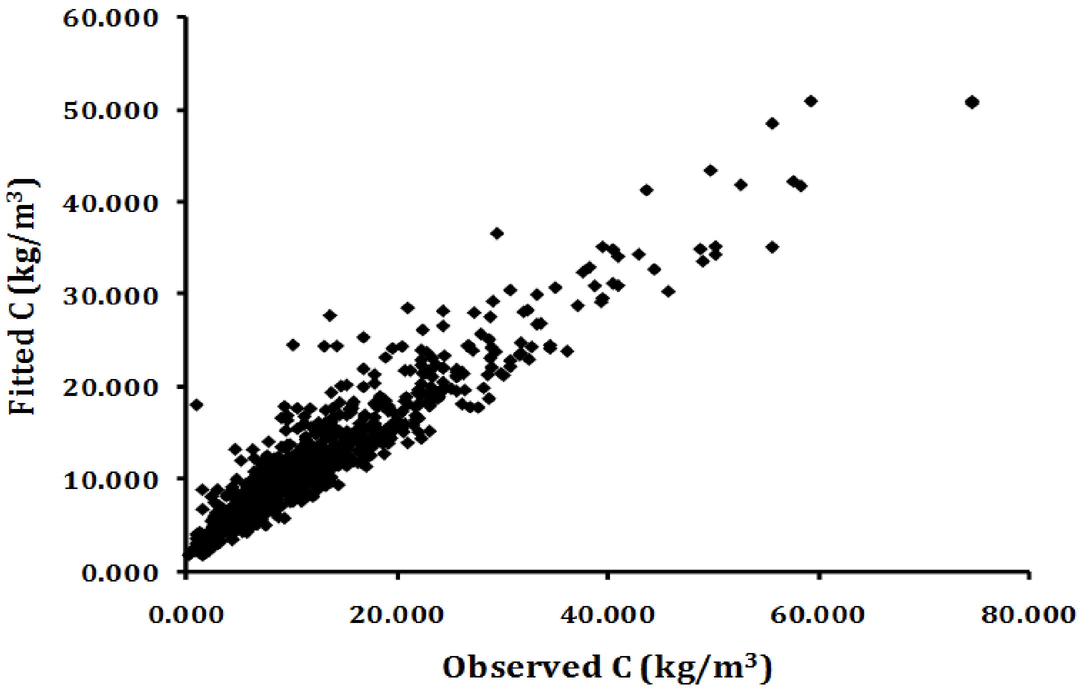


Figure 3.4: Observed vs Model values

3.3.3 Prediction of Exponential depth function parameters

The parameters of the exponential model viz. SOC_a, SOC_b and k were first log transformed to improve their normality. These parameters were then trained and predicted by Random Forest model. Descriptive statistics of out of bag mean square error (MSE_{OOB}) for each of the predicted parameters as estimate by RF are shown in Table 3.3. The mean MSE_{OOB} for Log (SOC_a), Log (SOC_b) and Log (k) were 0.03, 0.04 and 0.75 respectively.

Table 3.3: Out of bag mean square error (MSE_{OOB}) of parameters of exponential depth function.

Parameter	Indices	Mean	Median	SD	Minimum	Maximum
Log(SOC_a) (kg/m^3)	MSE_{OOB}	0.03	0.03	0.0003	0.03	0.04
Log (SOC_a) (kg/m^3)	MSE_{OOB}	0.44	0.44	0.002	0.43	0.44
Log(k)	MSE_{OOB}	0.75	0.75	0.004	0.74	0.76

3.3.4 Variables importance to SOC_a, SOC_b, k

Variables importance revealed the dominant factors influencing the soil organic carbon (Figure 3.5). The relative importance of climate, topographic and vegetation variables differs in RF models. SOC at the soil surface (SOC_a) was mainly influence by elevation and landuse. Other topographic parameters viz. slope, multi-resolution index of valley bottom flatness were also relevant to surface SOC (SOC_a.). The distribution of SOC with depth (the parameter k) is mainly influenced by mean annual average temperature, aspect and landuse. As for SOC at lower depth (SOC_b), the main influencing factors were found to be landuse, elevation and NDVI.

The variables in Figure 3.5 represents elevation, Multi-resolution of Ridge top flatness(MRRTF), Multi-resolution index of valley bottom flatness (MRVBF), slope gradient, slope aspect, profile curvature, plan curvature, Slope length(SL) Topographic Wetness Index (TWI), catchment area(CA), Mean annual precipitation(MAP), normalized difference vegetation index (NDVI), Mean annual average temperature ($T_{average}$), Difference between maximum and minimum temperature ($T_{differences}$), and Landuse landcover (LULC).

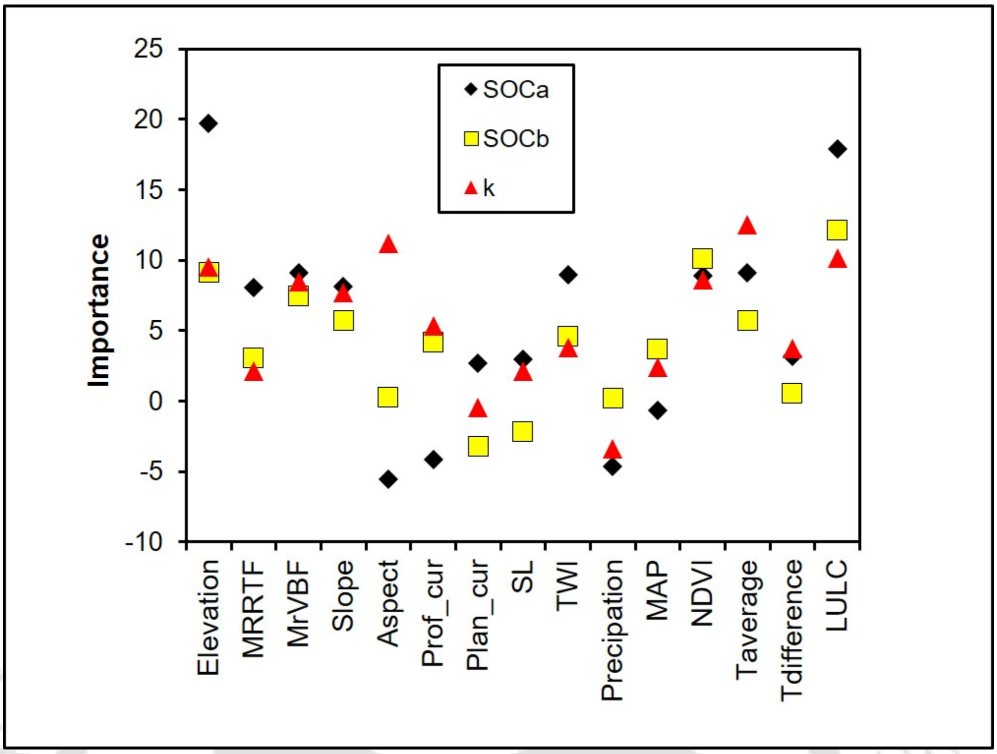


Figure 3.5: Variable importance.

3.3.5 Validation of prediction Model

Soil dataset derived from NBSS and LUP were randomly divided into training data set (143) and test data set (62). The predicted model was then evaluated on the training data set and on the test data set. Additionally, the model was also tested on 34 independent data set collected from field sampling. The model predict reasonably well with root mean square error ranging from 0.80-2.41 kg/m^2, mean square error range from -0.08 to -0.95 kg/m^2 for training data, test data and field data sets (Table 3.4). Negative values of ME indicated that the model is somewhat negatively biased.

3.3.6 Moran's I statistics of exponential depth parameters

Result (Table 3.5) indicated a positive spatial autocorrelation among the parameters. This result is in agreement with the assumption use by ordinary kriging, which assume that the variables are spatially correlated. Hence kriging was used to interpolate the parameters of the exponential function across the study area.

Table 3.4: Mean error (ME) and root mean square error (RMSE) of soil carbon stock (kg/m^2) for training, test and field data sets

	Indices	Mean	Median	SD	Minimum	Maximum
Training data	ME	-0.08	-0.08	0.006	-0.09	-0.06
	RMSE	0.80	0.80	0.004	0.79	0.82
Test data	ME	-0.61	-0.61	0.003	-0.62	-0.60
	RMSE	1.21	1.21	0.004	1.19	1.23
Field data	ME	-0.95	-0.95	0.003	-0.96	-0.94
	RMSE	2.41	2.41	0.004	2.39	2.42

SD: Standard Deviation

Table 3.5: Moran's I statistics of exponential depth parameters

Parameters	Moran's I	P
SOC_a	0.094	0.0010
SOC_b	0.156	0.0020
k	0.183	0.0020

3.3.7 Mapping of SOC storage

Using the predicted parameter of exponential function, we generate maps showing the distribution of SOC across the study area. As predicted, SOC content was found to be higher at the top surface and decreases with depth. When comparing the spatial distribution map of SOC (Figure 3.6) with topography and landuse map (Figure 3.7), we observed that areas with higher SOC content are generally at higher elevation and of forest cover, which signifies the dominant influence of elevation and landuse on SOC storage in this area.

3.4 Discussion

As information on global soil carbon data is becoming more important, there is a need to develop low cost methods to quantify and monitor changes in SOC. In this study, digital soil mapping using a combined approach of soil depth function and random forest were carried to predict the SOC distribution of NE India. As per the author's

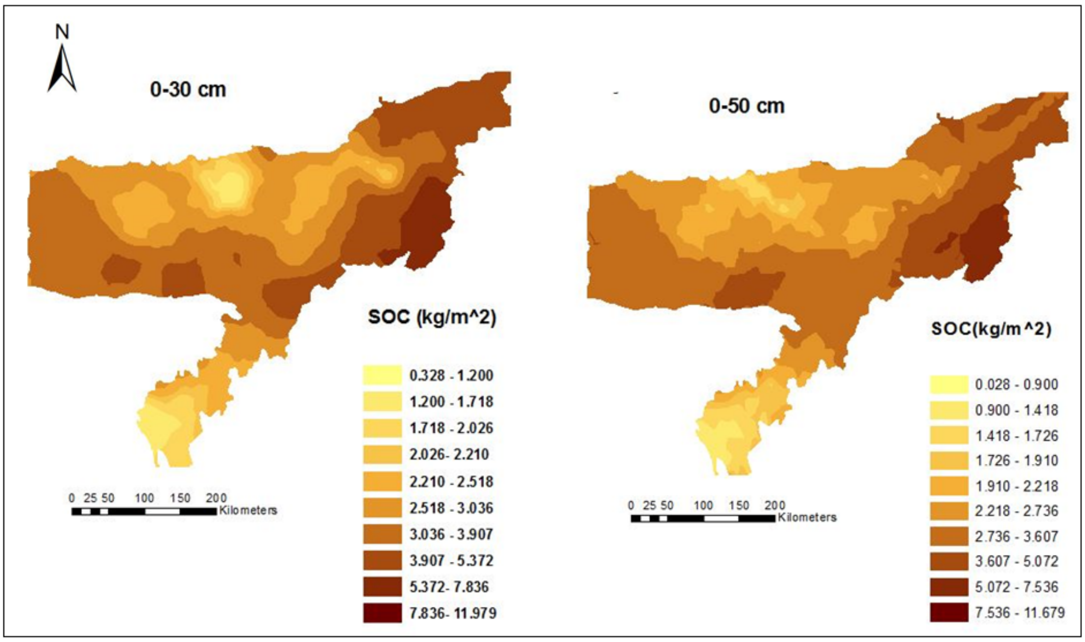


Figure 3.6: Spatial distribution map at 0-30 and 0-50 cm

knowledge, this is the first attempt to map the SOC stock in the world's rainiest region using digital mapping technique. The findings from this study indicated good results for the application of this technique to predict SOC stock even with less ground data for the mountainous and inaccessible area of NE India. Thus the method could prove to be useful as compared to data driven method carried by other researchers to map SOC stock in some parts of NE regions (Goyal, 2014; Ramesh et al., 2016; Thokchom and Yadava, 2016), as it removes the task of excessive soil sampling especially in areas like NE India which are difficult to access.

3.4.1 Variables important for SOC prediction

The total amount of carbon deposited in the soil depends on numerous factors, viz. climate (Hobley et al., 2015), topography (López-Vicente et al., 2009; Brevik, 2012), vegetation(Yang et al., 2008), parent soil material(Dai and Huang, 2006) and soil management (Luo et al., 2010).Also their relative influence on SOC formation varies with location and scales (O'rourke et al., 2015). Many researchers (Parton et al., 1987; Tian et al., 2000; Wang et al., 2014; Gray et al., 2015) reported that among these various factors, climatic variables account for most of the variation in soil carbon. Whereas, studies that were carried out by Swamp et al. (1999); Kaul et al. (2009); Wang et al.

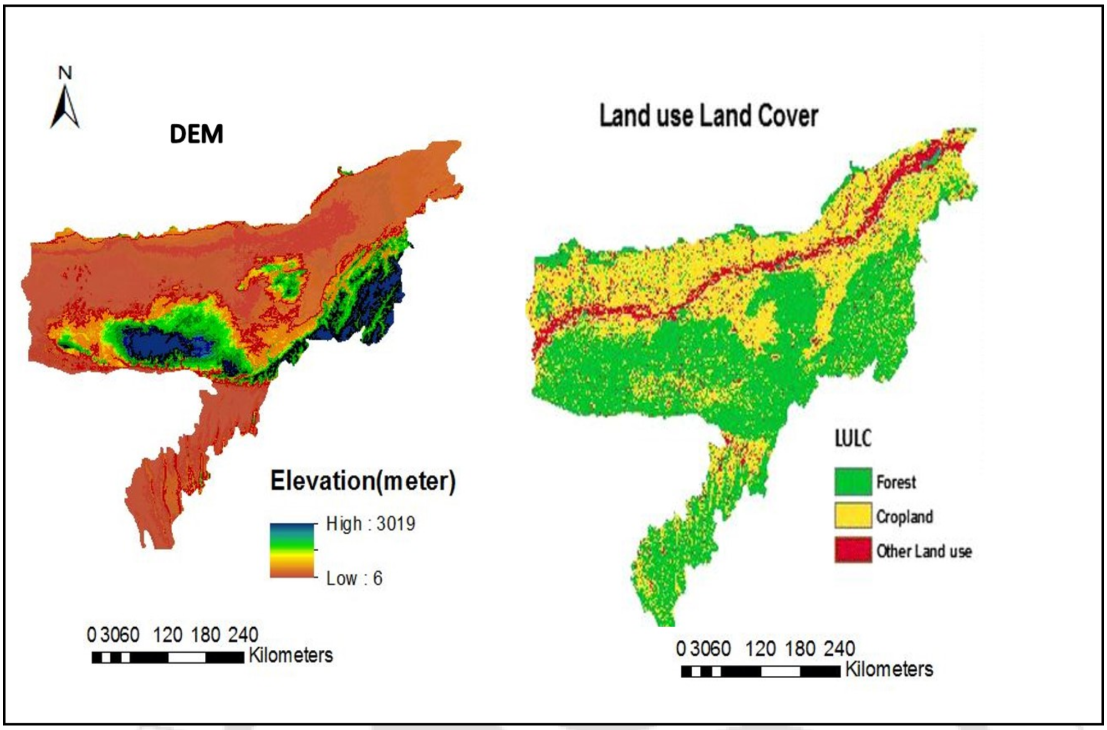


Figure 3.7: DEM and Landuse Landcover map of study area

(2001); Wei et al. (2008) reported that landuse and topography to be the dominating factors in controlling SOC distribution on a hillslope and small scale studies.

Similar to the above finding, our results indicate that elevation and landuse are the main important factors for predicting SOC of NE India at the soil surface using Random Forest. The relation between SOC at the surface and elevation might be that with the increase in elevation there is reduction in temperature which reduced the decomposition rate of SOC content (López-Vicente et al., 2009). A positive correlation between SOC at the surface and elevation was also observed by other researchers (Ruiz Sinoga et al., 2012; Brevik, 2012). The effect of the landuse and land cover on SOC content in the NE region of India was also observed by Choudhury, B. U., Das, P. T. and Das (2011) who reported that soils under grassland and dense forests have very high SOC (<2.5%) in comparison to cultivated areas (1.45-1.69%). Another important observation from this study is the relative importance of precipitation in predicting the SOC stock of NE India. Many previous studies indicate that rainfall was the main driver of SOC stock due to its ability to influence and determine the vegetation types, plant productivity and the rate of microbial decomposition of organic matter (Jobbágy and Jackson, 2000;

Yang et al., 2007; Wang et al., 2016). However, despite the fact that NE India receives the highest amount of rainfall in the world, the impact of precipitation on the SOC of this region was found to be limited compared to other factors like elevation, landuse and NDVI. The reason may be the effect of precipitation is already represented in the form of elevation. Elevation affect precipitation significantly especially in mountainous region like NE India. Generally, in mountainous regions, most of the rainfall lands on the windward side of the mountains, leaving the other side of the mountains with less amount of rainfall. Thus elevation maintains the temperature and precipitation of a region, which determine the types of plants and animals of a place, that ultimately define the amount of SOC present in a soil (Phachomphon et al., 2010).

The distribution of SOC with depth (the parameter k) is mainly influenced by mean annual average temperature, aspect and landuse. Aspect induced temperature and create microclimate in a region (Desta et al., 2004), thus temperature and aspect affects the depth distribution of soil organic carbon, possibly due to their effect on the rate of decomposition and dissolution of organic carbon content (Toosi et al., 2014). The results are in agreement with the findings previously reported by Hobley et al. (2015). As for SOC at lower depth (SOC_b), the main influencing factors were found to be landuse, elevation and NDVI. Various management practices on different landuse may affect the distribution of SOC with depth. NDVI which indicated the amount of biomass and vegetation cover (Yang et al., 2016) shows a relative importance to all the three parameters of exponential function (SOC_a, SOC_b, k). Yang et al. (2008)reported that SOC can almost be determined by the presence of vegetation alone and can be used as a proxy for determination of SOC content.

3.4.2 Model Performance

The model was evaluated using MSE and RMSE indices (Table 3.4). Researchers have shown that the accuracy of the model determined by comparing the original data and the estimated data at the calibration sites often over estimates the real prediction of the model (Bobryk et al., 2016). Thus the model is validated with the test data set that was partitioned from the original data set and with 34 data collected from field sampling up to 15cm depth. Even though the MSE and RMSE (Table 3.4) increases with the test data set and independent data set, the model was able to provide an acceptable estimate of SOC stock with a mean RMSE of 1.21 and 2.41 kg/m^2 for test and independent data set. The results are comparable with previous studies related to digital mapping, such as Mishra et al. (2009) (RMSE: 2.57-3.93 kg/m^2), Yang et al. (2016) (RMSE: 0.94 kg/m^2).

Looking at some of the limitations involved in prediction of SOC in this study, the prediction of SOC stock was validated using just 34 samples taken from a small region located in Meghalaya. This may bring biased to the model, hence, future study should concentrate on collecting more samples from the entire study area that are taken from various landscape position, slope, steepness to validate and improve the model. Also bulk density values of trained samples were predicted from pedo-transfer function, which may create error in the prediction. Likewise, the SOC samples were not taken uniformly, thus SOC at sparely samples location may produce prediction errors.

Table 3.6: SOC of various soil type in the study area

Soil type of the study area (As per NRSC classification)	**SOC (%)**
Clay	2.01
Clay Loam	1.60
Loam	1.38
Loamy sand	1.27
Sandy clay loam	1.33
Sandy Loam	1.19
Silt Loam	1.30
Silty Clay	1.72
sandy Loam	1.92

Also the 218 soil samples extracted from National Bureau of Soil Survey and Landuse Planning website were from different soil type. Many literatures(Adhikari et al., 2014; Tiwary et al., 2015) reported that soil type is an important factor in accessing SOC characteristics. As seen from Table 3.6, SOC in the study area also vary with soil types. This table is generated from the raw data obtained from National Bureau of Soil Survey and Landuse Planning as shown in the appendix Table A1. Also, the data in the appendix Table A1 indicates that the soil type varies continuously in space. As the soil map that is available to us is of course resolution, using information from this map may provide wrong output to the model.Hence soil type was not used in the present study. However, future study can be improved by first generating spatially distributed information on soil classes or soil types then use the information on soil type as one of the predictor of SOC.

3.5 Conclusion

Since soil organic carbon vary greatly in space and time, soil carbon map produced from statistics of few sample locations may overestimate the SOC stocks of a region. Thus the use of pixel based approach as demonstrated in this study, would be more reliable in determining and monitoring changes of SOC in NE India as a function of topography, landuse, vegetation and climatic variables. With pixel based approach, the present study predicted the SOC stock across the study area and generated maps which provide detailed information of SOC stocks distribution. The results from the study also enhance our knowledge over the role of landuse on SOC storage in the study area, thus denoting the potential opportunities to use land management as a ways to improve the SOC storage of this region. Information from this study can be also useful for identification of potential regions for soil carbon sequestration. It can help the policy makers in management and monitoring of natural resources and can serve as an input for further research modeling and simulation studies.

CHAPTER 4

Altitudinal pattern and its control on plants and soil carbon concentration

4.1 Introduction

Among the soil organic carbon controlling factors, altitude is one of the most used in soil mapping, because of its strong correlation with spatial variability of SOC over a landscape. Many studies(López-Vicente et al., 2009; Vieira et al., 2011) that carried out the analysis of changes in SOC along an elevation gradient, have reported that SOC increased significantly with increase in elevation as air temperature decreased with altitude which likely limits the decomposition and other soil microbial activities. Few other (He et al., 2016) reported that in addition to low temperature, the presence of high litters and roots in high elevation areas helps in explaining why SOC increase with elevation. Some of the latest experimental studies(Fornara and Tilman, 2008; Lange et al., 2015; Chen et al., 2018) have reported that presence of higher plant species richness helps in reducing carbon losses from deposition and provides more carbon inputs in the form of below ground biomass as well as help in increasing the soil microbial activity and diversity which helps in elevating the amount of SOC storage. However, although many of these studies have reported the likely mechanism that may explain the effect of elevation on SOC, the exact pathway on how elevation directly or indirectly affect SOC is yet to be understood. Besides, SOC status and its underlying mechanism may also vary among different ecosystem type along with an elevation gradient(Sundqvist et al., 2013). With this complexity, our understanding of the mechanism on how SOC varies with elevation is thus still limited.

In the previous objective, altitude was also found to strongly influences the distribution of soil organic carbon (SOC) storage in our study area. Study across the globe (Girardin et al., 2010; Kitayama and Aiba, 2002) stress the importance of site selection, as the underlying mechanism may vary among different ecosystem type. Therefore, as Northeast India has a great diversity of land form type, it may be wrong to generalized the underlying mechanism of altitude on SOC if we carry the analysis on the entire NE region. Hence this analysis was carried out only along the three elevation range of undisturbed forest stand of Meghalaya.

A total of 45 undisturbed plot of 10 $\times$ 10 m^2 in size were chosen to assess the SOC concentration along this three elevation gradient. Our principal hypothesis was that SOC concentration would change along the chosen elevation gradient. In particular, the present study applied path analysis to evaluate the path that may explain the relationship between SOC and explanatory variable in the study area based on various hypothesized pathways reported in the literature.

4.2 Materials and Methods

4.2.1 Study area

The study was carried out in three altitude zone of forest stand of Meghalaya(Figure 4.1) with elevation range from 748-1133 meter located in Shillong bypass towards Barapani (25.56-25.64°N and 92-92.20°E), 1133-1458 in Jaintia Hills towards Jowai (25.45-25.54°N and 92.17-92.25°E) and 1458-1917 in East Khasi Hills toward Laitkor near Shillong peak and North-Eastern Hill University Campus (25.51-25.56°N and 91.83-91.96°E). In all the three elevation gradients, forest canopy was majority solely composed of pine trees *(Pinus kesiya)*. However, a few other trees species were found scattered along the pine trees along with grass, herbs, ferns, shrubs.

4.2.2 Experimental soil sampling

For this analysis, fifteen undisturbed forest sites were chosen randomly from each of the three elevation range. At each of these sites, a sample plot of 10 $\times$ 10 m^2 was established. Four samples in a zigzag manner (Figure 4.2) were collected within each

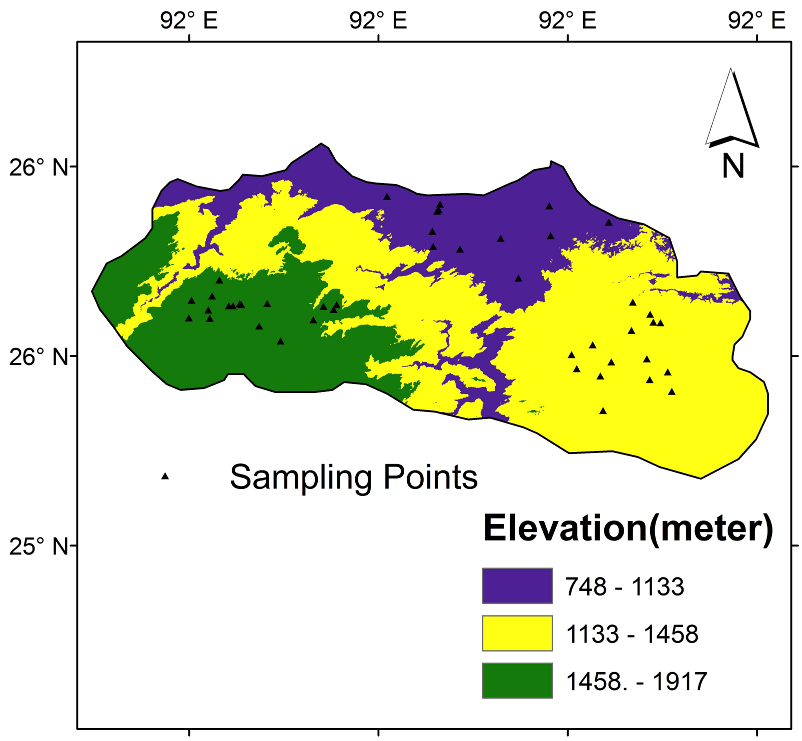


Figure 4.1: Soil sampling locations along the three choosen elevation range

plot and mixed to form composite soil samples. (Total no of soil samples= 15 sites $\times$ 4 samples $\times$ 3 elevation range).All the sites were north exposed and having a mild slope in order to minimize the effect of slope and aspect on soil properties. The depth of soil sampling was up to 30 cm. Same depth across the sites was chosen so that uniform comparison can be made between the studied soil sample, in order to avoid error as soil carbon is known to vary with depth. The coordinates (latitudes and longitudes) of each location were obtained with the help of global positioning system (GPS). The soil samples from the 30cm soil layers taken with the help of soil auger are then stored in a labeled zip lock plastic bag. Core cutter method was used to calculate the bulk density of the soil. All samples were then air-dried, sieved through 2 mm sieves, and stored for further analysis. 2-mm sieved soil is used in analysis because it includes all primary soil particles (sand, silt, and clay) and it excludes bigger soil aggregates wherein SOC or other elements/nutrients/variables may be physically protected, and may not be extracted in short analytical procedures, under-estimating thereby the values/status of the nutrient of interest. The soil sample was analyzed in a laboratory for SOC using Walkley and Black rapid titration method (Walkley and Black, 1934). The procedure

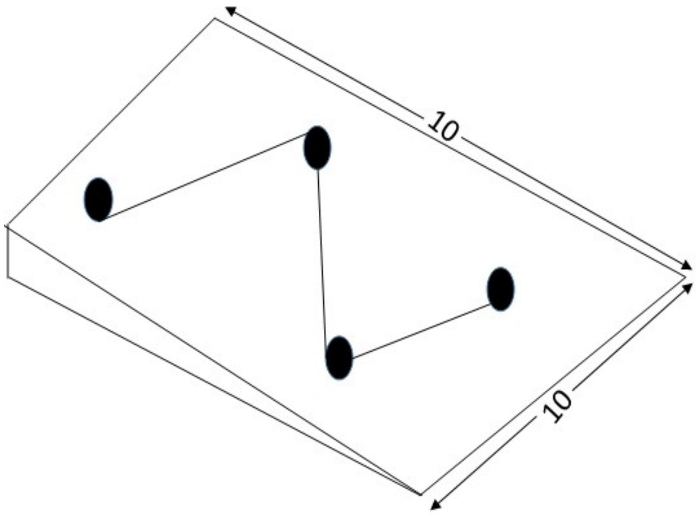


Figure 4.2: Locating area to take sample along a 10 × 10 m^2

for this analysis is as described in the previous objective. SOC stock is calculated using the following equation

$$\text{SOC (t C/ ha)} = \text{SOC(\%)} \times \text{BD (g/cm}^3) \times \text{SD (cm)} \tag{4.1}$$

$$\text{SOC(kg/m}^2) = \text{SOC (t C/ha)} \times 0.1 \tag{4.2}$$

where SOC - Concentration of soil organic carbon (%); BD - Bulk density (g/cm^3); SD-soil sampling depth (cm). If there is gravel in the soil, SOC (%) is first adjusted before calculation.

4.2.3 Temperature, Precipitation, and Soil moisture data

The average annual precipitation and temperature with a 0.25°× 0.25°resolution for a period of 1985-2015 were obtained from India Meteorological Department (IMD), Pune. Soil moisture was calculated by weighing the soil sample before and after oven drying at 105°C for 24 hours.

4.2.4 Vegetation Data

In each quadrant of the three elevation stand, the number of type of tree species, shrubs, herbs, medical plants, grass were identified which is used as a measure of species richness per quadrant of 10 m × 10 m. Thus species richness here refers to the number of species per plot. Total standing biomass or vegetation cover in an area signifies the ecosystem productivity and can be assumed to be the proportion of carbon inputs into the soils (Kunkel et al., 2011). The total biomass in an area can be referred to as plant density and the measurement of the variation of plant density can be defined using Normalized vegetation index(NDVI). Therefore, annual NDVI value obtained from MODIS were used in this study to infer to the variation of vegetation density in the study area.

4.2.5 Data Analysis

The relationship between elevation, average annual temperature, average annual precipitation, SOC density, SOC stock was evaluated using linear regression analysis. Correlation between SOC and climatic variables, all plants, and soil measurements were tested using Pearson's correlation method. The variables were tested for statistically significance relationship both at $P<0.05$ and $P<0.01$. Correlation analysis is followed by path analysis.

4.2.5.1 Path Analysis

The method of Path coefficient analysis was introduced by Wright (1934).This method is based on a series of multiple regression analysis with the additional assumption that there exist a causal relationship between the dependent and independent variables. In simple terms, the Path analysis involves testing a theoretically or empirically defined pattern of relationship among a set of variables.

For instance, we are working with four variables A, B, C, and D. Then using path analysis we can test the relationship among these variables as defined by some hypothesis or theory which are based on prior experience or empirical evidences. For example, if the defined hypothesis state that A is a variable that may cause changes in both B and C, and B and C are the variables responsible for change in D. It is also assumed that A has some direct effect on D also. Then we can specify the relationship among the said variables as stated above and test it based on regression analysis. The said model is represented in the form of Path diagram and we'll test this model of relationship using multiple regression analysis(Figure 4.3).

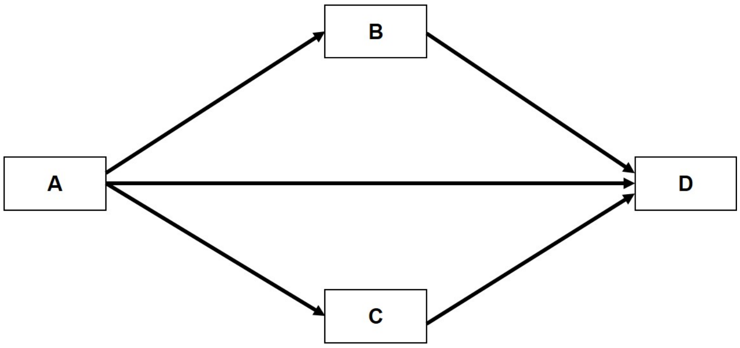


Figure 4.3: Path Analysis diagram

Similarly, in our analysis, we applied path analysis to explore the hypothetical pathway that may explain how elevation influences the carbon content in the soil. We run the model with a different hypothesis as described below that results in different path models.

Hypotheis

The different hypothesized pathways reported in the literatures are:

Plant species richness will have a positive relationship with SOC: Plant species richness enhances SOC storage through enhanced biomass production(Cong et al., 2014)

Soil moisture will have a positive relationship with SOC: Given the same amount of carbon inputs (e.g. litterfall), the presence of higher amount of soil moisture inhibits the decomposition of organic matter in soil by reducing the respiration of soil microorganism because of less availability of oxygen (Silver et al., 1999) leading to higher soil carbon storage.

NDVI will have a positive relationship with SOC:Higher standing biomass increase carbon inputs(e.g. litters) and lead to higher soil carbon storage (Kunkel et al., 2011)

Temperature, Precipitation will have a positive relationship with Plant diversity: Precipitation, temperature supply water, energy and the difference in the amount of precipitation or temperature control plants diversity (Hawkins et al., 2003)

Elevation-Temperature-SOC:As elevation increases, temperature decreases. The differences in temperature along elevation gradients control the soil carbon balance through carbon decomposition and lose from the soil. (He et al., 2016)

Precipitation-Soil moisture-NDVI-Soil carbon: Rainfall replenish the soil moisture of the soil which affects the seasonal distribution and activities of plants and affects the carbon storage in the soil (Sponseller, 2007)

Temperature, Precipitation-soil moisture:Precipitation recharge the soil moisture, whereas higher temperature leads to more soil water evaporation (Trenberth, 2011)

Elevation-Soil moisture: In relatively low slope of mountainous soil, soil moisture increase with an increase in elevation because of orographic effect and year-round cloudiness. However, in the steeper slope, it may be the opposite as more water is drained with gravity(Wang et al., 2002)

The results of this testing has two important components. The first is the overall fit of the model.This is assessed using the available fit indices, in our case we used Chi Square test. For a model to be called good fit, the Chi square should be non significant, the chi square to degree of freedom ratio should be less than 5 (Grace, 2006). The second important component of the results involve testing the significance of the paths and this should be done when there is an evidence that the overall model is fit. This includes testing of significance of direct effects (paths) and indirect effects. Depending on the outcome of the analysis, only variables with significant effect are retained. For all the models considered, the adequacy of the selected pathway and the data was validated using the residual mean square error of approximation.

4.3 Results

4.3.1 Sites properties along the elevation gradient

The average temperatures of the sites were observed to decrease along the elevation gradient at the rate of 0.0019°C (Figure 4.4 A). However, precipitation was observed to increase with an increase in altitude at the rate of 0.1206 cm (Figure 4.4 B). . Elevation was observed to have a significant positive correlation with precipitation and soil moisture and a significant negative correlation with temperature (Table 4.1)

4.3.2 Soil carbon values along the elevation gradient

The soils of the undisturbed forest soil of the three elevation zones were all acidic in nature, having 2.43 to 3.38 % of mean soil carbon value, 4.93 to 6.68 kg/m^{-2} average soil

Table 4.1: Relationship between climatic variables, all plants and soil measure using Pearson's correlation (r values)

	Elevation	**Temperature**	**Precipitation**	**Soil moisture**	**Plant diversity**	**NDVI**	**SOC**
Elevation	1	-.779**	.627**	.486**	.635**	-.355*	.595**
Temperature	-.779**	1	-.920**	-.340*	-.530**	.252	-.487**
Precipitation	.627**	-.920**	1	.254	.396*	.127	.423**
Soil moisture	.486**	-.340*	.254	1	.566**	-.212	.783**
Plant diversity	.635**	-.530**	.396*	.566**	1	-.370*	.657**
NDVI	-.355*	.252	.127	-.212	-.370*	1	-.157
SOC	.595**	-.487**	.423**	.783**	.657**	-.157	1

****.Correlation is significant at the 0.01 level**

***.Correlation is significant at the 0.05 level**

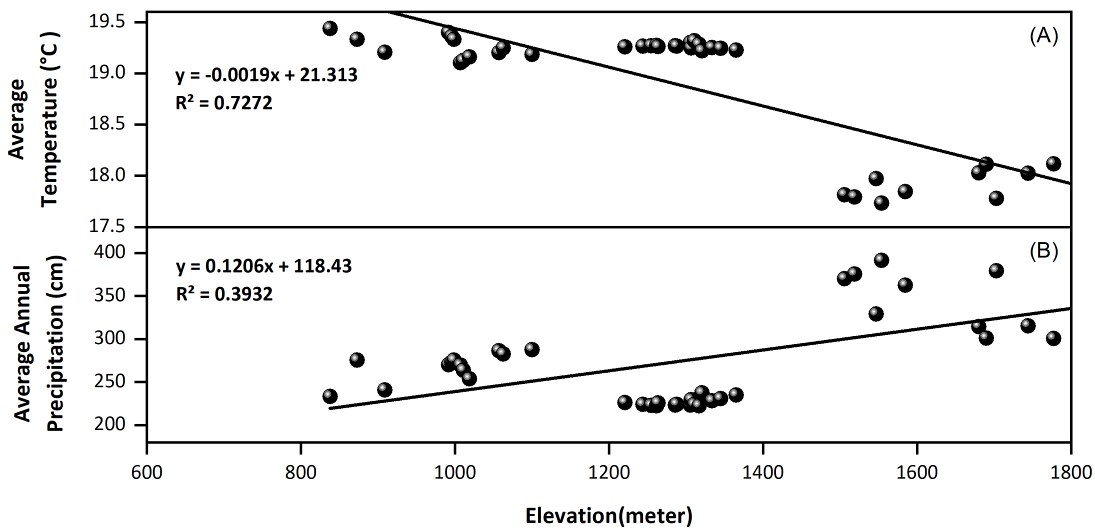


Figure 4.4: Average annual temperature (A), average annual precipitation (B) and soil moisture (C) along an altitudinal gradient in forest biome of Meghalaya, India

carbon stock, 1.29 to 1.35 g/cm^3 of bulk density and 5.23 to 5.32 pH value (Table 4.2) which falls within the same range reported by other studies in Northeast India such as Tripathi et al. (2004) (SOC =1.77-3.2 %),Choudhury et al. (2013) (SOC=2.5-3.5 %).SOC was found to also correlated with other variables as shown in Table 4.1.

4.3.3 Vegetation community and diversity along the elevation gradient

In all the three elevation gradients, forest canopy was majority solely composed of pine trees *(Pinus kesiya)*. However, a few other trees species were found scattered along the pine trees along with grass, herbs, ferns, shrubs. Few of the broad leaves trees observed were *Rhododendron arboretum, Emblica offinalis, Prunus domestica, Schimawallichii, Docynia indica, Brucea javanica.* Some of the shrubs species found in these three forest stand included *Myrsine semiserrata, Brucea javanica, Solanum torvum, Fiscus Auriculata, Rubus ellipticus.* The forest floor is covered with grass, ferns, herbs and flowering plants. Some of these include *Anthyrium drepanopterum, Lantana camara, Bidens pilosa, Cyperus rotandus, hedychium coccineum, Ageratina adenophora, Rubus monogynus, Galinsoga parviflora, Lindenbergia hispida.* Species richness per quadrant (total no of tree species, shrubs, herbs, medical plants, grass) was observed to increase with elevation and have a positive correlation with SOC stock (Figure 4.5)

Table 4.2: Soil characteristics of the undisturbed forest soil of three altitude zones (mean ± SEM)

Soil Properties	**Altitude zones (A1)**	**Altitude zones (A2)**	**Altitude zones (A3)**
SOC (%)	2.43 ±0.13	2.79 ±0.21	3.38 ±0.09
SOC (kg/m^2)	4.93±0.23	5.57±0.38	6.68±0.17
Bulk Density (g/cm^3)	1.35±0.87	1.30 ±0.92	1.29 ±0.72
pH	5.23 ±0.08	5.17±0.06	5.32±0.07

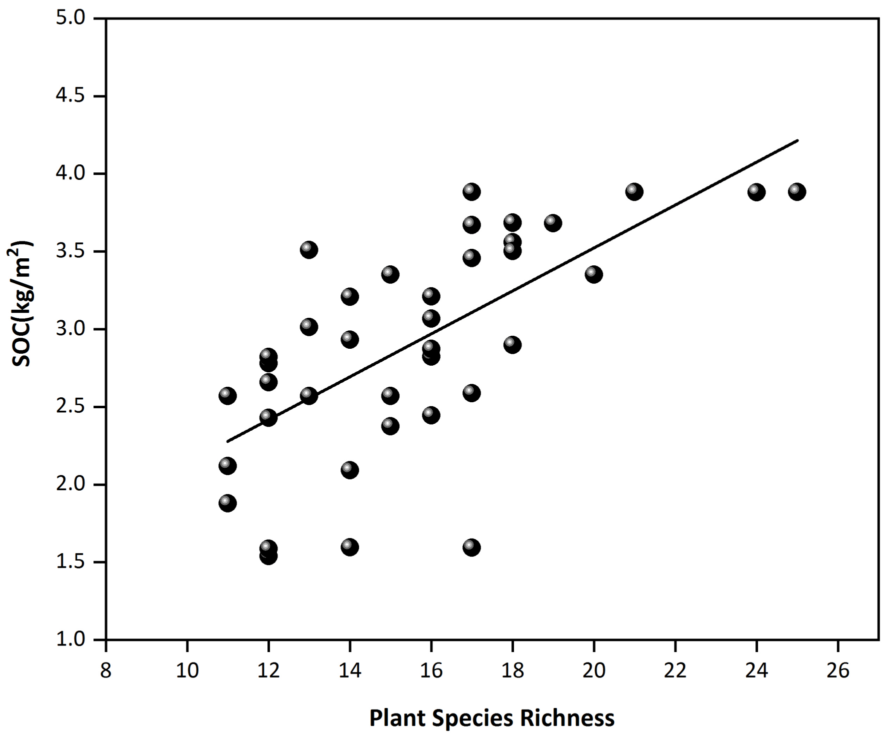


Figure 4.5: The relationship between plant species richness and SOC(kg/m^2)

4.3.4 Mechanism of soil carbon storage along an elevation gradient

According to path analysis (Figure 4.6), there was no direct relationship between elevation and soil carbon. The model shows elevation had an indirect positive effect on soil carbon through soil moisture, temperature, and precipitation which influences the plant species richness and density and ultimately affect the soil carbon storage. Soil moisture had a direct and positive effect on soil carbon (β = 0.50) and also an indirect effect via its influence on plant species richness (β = 0.36×0.40=0.14); the net effect of soil moisture on SOC was positive (β =0.50+0.14= 0.64). The effect of elevation on SOC via soil moisture is a positive effect (β =0.49×0.64=0.31). Precipitation had no direct effect on SOC, but had an indirect via its influence on plant species richness (β =0.38×0.40=0.15) and plant density (β =0.87×0.27=0.23); the net effect of precipitation on SOC was positive (β =0.23+0.15=0.38). The net effect of elevation on SOC via precipitation was positive (β =0.63×0.38=0.24). Similarly, the temperature had a direct and negative effect on SOC (β =-0.37) and also an indirect effect via its influence on plant species richness (β =-0.70×0.40=-0.28) and plant density (β =0.89×0.27=0.24); the net effect of temperature on SOC was negative (β =-0.28+0.23-0.37=-0.42). The effect of elevation on SOC via temperature is positive (β =-0.42×-0.78=0.32). Thus the net effect of elevation on SOC (β =0.32+0.31+0.24=0.87).

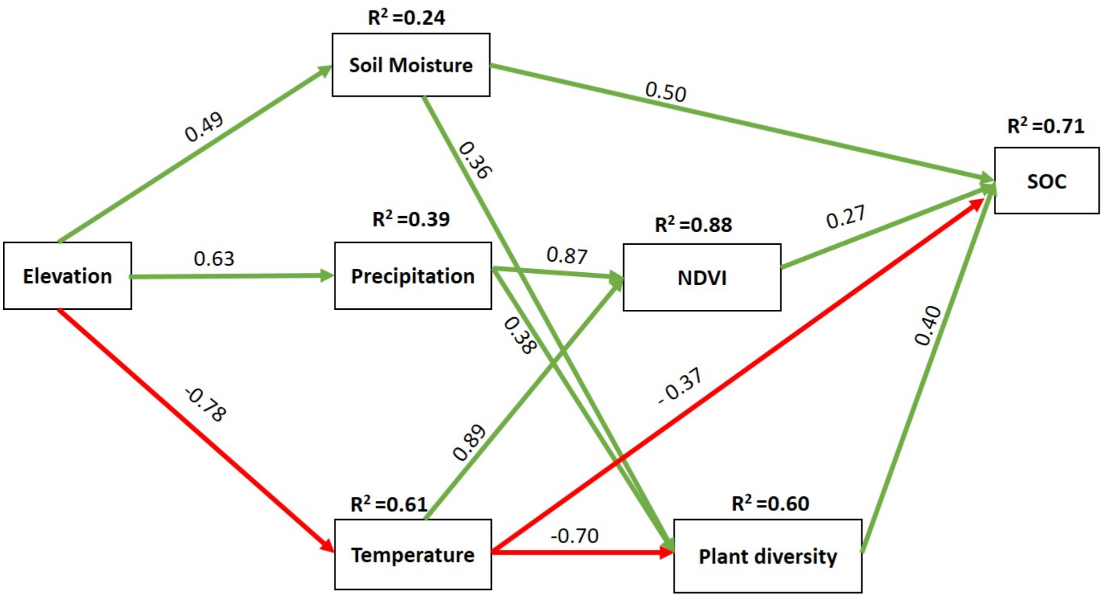


Figure 4.6: Path analysis of the changes in SOC concentration. The green line indicates positive path whereas the red line indicates a negative path

4.4 Discussion

As predicted, changes in elevation result in changes in soil carbon concentration. Changes of nutrients status with elevation such as that of SOC concentration are reported to vary among different ecosystem types(He et al., 2016). In the study area, SOC was found to increase significantly with altitude (r=0.595**) in an undisturbed forest biome mostly composed of pine trees. This results confirmed the finding of some earlier study carried out in India(Tripathi et al., 2004; Charan et al., 2012; Choudhury et al., 2013). Although many of these previous studies have reported the effect of elevation on SOC, the exact pathway on how elevation directly or indirectly affect SOC especially in the mountainous region is yet to be understood. The present study attempted to understand the hypothetical mechanism that may explain the effect of elevation on SOC through path analysis based on various potential relationship reported in the literature. The result of the path analysis model (Figure 4.6) indicated that there is no direct relationship between SOC and elevation in the study area. The model instead indicated that elevation had an indirect positive effect on soil carbon through soil moisture, temperature, and precipitation which influences the plant species richness and density and ultimately affect the soil carbon storage.

The average temperature of the sites was observed to decrease along the elevation gradient, however, precipitation was observed to increase with an increase in altitude (Figure 4.4A). The outcome of the study bolstered the conventional theoretical predictions and findings that SOC concentration is predominantly controlled by the ideal climate conditions of an area(Chen et al., 2018; Yang et al., 2007). The strong negative effect between temperature and SOC storage as observed both from correlation results and path analysis suggest that carbon losses through soil microorganism respiration (heterotrophic respiration) could play a major role in controlling the SOC storage of forest biome in the study area. The present study also found that the favorable climate in the high elevation area (low temperature and high precipitation) as compared to lower elevation was found to result in more localized species ranges and hence higher species richness and plant density which had a positive effect on SOC storage. The relation between SOC and plant species richness and density may be that the presence of higher plant species richness and density helps in reducing in carbon losses from deposition and provides more carbon inputs in the form of belowground biomass as well as help in increasing the soil microbial activity and diversity which helps in elevating the amount of SOC storage as reported by some of the latest experimental studies conducted across the world(Fornara and Tilman, 2008; Lange et al., 2015; Chen et al., 2018).Tripathi et al. (2004) in their studies of tree distribution in Meghalaya reported that at high elevation stand (1900 m), mid-elevation (1460 m) and low elevation stand (1050 m), 134,54 and 93 plant species were recorded. Thus the present study is in accordance with their study, where we observed that favorable climate at higher altitude leads to more species richness. Another finding of the study is the indirect positive effect of elevation on SOC mediated by soil moisture. A significant positive correlation between soil moisture and elevation (r=.486**) in mountainous forest biome may be attributed to orographic effect and year-round cloudiness(Wang et al., 2002). The presence of higher amount of soil moisture, in turn, inhibits the decomposition of organic matter in soil by reducing the respiration of soil microorganism because of less availability of oxygen(Silver et al., 1999) leading to higher soil carbon storage, given the same amount of carbon inputs (e.g. litterfall). Hence, the soil in higher elevation often reported having a higher amount of organic carbon input in the form of litterfall, although they may actually have less litter fall than that of lower elevation area with low moisture content (Scatena and Lugo, 1995).

It may be noted that all the sites selected for this study were north exposed and having a mild slope. Also, the soil properties in this study such as pH were similar, where all the soils of the three elevation zones were acidic in nature (Table 4.2). Study across the globe that were carried out on gentle slopes and similar soil properties also reported an increase of SOC with elevation(Girardin et al., 2010; Kitayama and Aiba, 2002) . In contrast study on steep slopes and changing soil properties do not report any relationship between SOC and elevation(Schrumpf 2001),(Soethe et al. 2007). In fact,Heckman et al. (2009) stress the important role of soil properties such as pH in controlling SOC dynamics. This underscores the importance of site selections and thus indicate that the results of this study or any other study can only be generalized based on similar sites properties.

4.5 Conclusion

This study shows that soil organic carbon increase with an increase in altitude, likely because of the presence of more favorable climate conditions at higher elevation sites leading to more diverse plants type and higher plant density. The outcomes of the study suggest that soil carbon storage can be significantly improved by fostering plant species richness and density. The presence of higher soil moisture content at a higher altitude which may likely inhibit the decomposition of organic matter in the soil is another reason that is observed to affect the storage of soil carbon in the forest biome of the study area. Results of this study have an essential implication for environmental management and for improving the existing carbon cycle model: planting and conservation of high plants species richness suitable for an area can help to improve soil carbon sequestration which will improve soil fertility as well as in mitigating the global warming.

CHAPTER 5

Carbon Fluxes from Landuse and Land management

5.1 Introduction

Vegetation and soil can both act as a source or sink to the atmospheric CO_2 (IPCC, 2006) and if properly managed can play a major role in combating the excess anthropogenic carbon emission (Lal, 2004b). Soil is one of the largest reservoir of organic carbon, and it can harbor carbon as much as twice the amount of carbon stored in the atmosphere (Lal, 2008). However, it has been reported that landuse management and landuse land cover(LULC) conversion can cause drastic change in the amount of carbon stored in the soil and vegetation (Jin et al., 2011; Deng et al., 2016) and as a result they may both act as a source to greenhouse gases (Powers et al., 2011).Around one third of carbon emission in the world is attributed to LULC conversion (Van der Werf et al., 2009), making LULC an important factor related to distribution and emission of carbon(Houghton, 2002). Landuse management such as control of man-made forest fire, control of plants diseases, control of pest, proper irrigation and proper usage of fertilizers in croplands, proper managements of grassland can affect the amount of carbon storage and carbon emission(Apps and Price, 2013).Thus LULC and landuse management together can greatly determine the extent and amount of carbon storage (Burton et al., 2002).

Across the globe, several studies have already been carried out to study the impact of LULC and land management on carbon emissions (Ravindranath et al., 1997; Swamp et al., 1999; Lai et al., 2016).However, most of these studies, focused on the ability of a particular single landuse to sequester carbon following its management (Kaul et al., 2009; Laganière et al., 2010), whereas, studies related to LULC conversion often focused only on a specified number of landuse (mostly forest and cropland) (West and Post, 2002b; Prasad et al., 2007). Landuse management of all types viz. grassland, forest land, agriculture land, other land and even built up areas, all play an important part in carbon cycle and must be given equal attention. To address the problem of climate change, proper management of all landuse across the globe is important to retain the existing carbon and to increase the uptake of atmospheric carbon.

Northeast region of India contains around one third of India's biodiversity(Jamir, 2015) and factors such as high average rainfall in this region offer a favorable conditions for carbon storage. This region being isolated from other regions of India has been able to preserve most of its biodiversity(Choudhury et al., 2013). However, with the population growth, the demand for food production and economic development has put pressure on landuse of this region. In the past few years, activities viz. agriculture expansion, deforestation, mining have led to the degradation of natural resources in this region (Lele and Joshi, 2009). These changes will continue in the future and will lead to alteration of carbon pools and sink of NE region; however, they are not often included in the landuse land management planning. Also knowing that landuse is one of the main factors influencing the SOC of Northeast(NE) India as shown in the previous objective, analysis of effect of landuse and various land management is therefore essential to have an insight of how carbon storage can change as a result of landuse changes and land management in NE region. To address this need, an attempt is made to study the influence of LULC and various land management on carbon storage in NE India. This chapter present the method and results of analysis of changes in carbon storage as a result of LULC and land management during a period of 2006 to 2013 in the states of Assam, Meghalaya, Manipur, Nagaland and Tripura in NE India.

5.2 Materials and Methods

5.2.1 Landuse data

Landuse map from 2006 -2013 were obtained from National Remote Sensing Center (NRSC) Hyderabad, in digital format on request. These maps were prepared using multi-temporal satellite of IRS AWiFS sensor on 1:250,000 scale (Refer to Appendix B). The obtained maps were then projected into UTM zone 46N. These maps were further reclassified into 6 broad landuse classes as per IPCC guidelines, viz. forest land, agricultural land, grassland, settlement area, water bodies and other land (Table 5.1)

5.2.2 Calculation of changes in biomass carbon stock

IPCC recommends two methods to estimate carbon stock changes as a result of LULC changes viz. the stock-difference method which measure the standing biomass stock at the beginning and at the end of study period as shown in Equation 5.1 and gain loss method which estimates the carbon emission as a difference of biomass gain on the basis of increment growth and biomass loss due to human activities as shown in Equation 5.2.

$$\Delta C = \frac{C_{t2} - C_{t1}}{t_2 - t_1} \tag{5.1}$$

Where, ΔC refers to annual change in carbon stock (t C/yr),C_{t2} refers to carbon stock in time t_2 and C_{t1} refers to carbon stock in time t_1

$$\Delta C = \Delta C_{Gain} - \Delta C_{Loss} \tag{5.2}$$

Where, ΔC refers to changes in carbon stock annually (t C / yr), ΔC_{Gain} refers to annual gain in carbon stock (t C / yr)and ΔC_{Loss} refers to annual loss in carbon stock (t C / yr)

5.2.3 Method to define Landuse for estimating the carbon stock change

There are two approaches to define landuse for estimating the carbon stock changes. Approach 1 defines land-use as total area within a defined spatial unit, and only the net changes in land-use area is tracked through time whereas approach 2 gives an estimation

Table 5.1: Categories of Landuse. (Obtained from bhuvan.nrsc.gov.in)

Main Categories	**Sub Categories**
Settlement	Urban areas Rural areas Mining areas
Agriculture land	Kharif crop Rabi crop Zaid crop Double/Triple crop Agricultural Plantation Current-shifting cultivation
Forest	Evergreen / Semi evergreen Deciduous Forest Plantation Scrub Forest Swamp / Mangroves
Grassland	Alpine/ sub alpine Temperate Tropical/ sub tropical
Wasteland/ barren/ other land	Scrub land (open and dense) Rann Barren Rocky Raveneous Land

of both the net losses and gains in the area of specific land-use category (i.e., changes both from and to that particular landuse category). These are presented in the form of land-use conversion matrix.

5.2.4 Activity data and calculation of emission factor

To estimate the change in biomass carbon stock, approach 2 along with stock difference method was followed using country regional specific data. Forest survey of India (FSI) (http://fsi.nic.in) provides growing stock volume of trees outside forest (TOF) for all the states in India, in its State Forest Report (SFR) across different years. TOF includes trees ($<$ 1.0 ha) in plantation, agricultural land, trees in urban areas, trees along the road and cropland. Growing stock volume here refers to the above-stump volume of living trees measured from the bark up to the tree tops. The amounts of growing stock of TOF for all the states used in this study are shown in Table 5.2.

Table 5.2: Growing stock of TOF (Million cumec)

State	**2006 (SFR 2009)**	**2013 (SFR 2015)**
Assam	42.44	33.018
Manipur	9.61	9.015
Meghalaya	23.47	19.08
Nagaland	13.93	12.197
Tripura	8.04	7.067

Change in biomass carbon is therefore estimated as per the stock difference method which is also followed by GHC platform India (Padmanabha 2016). Here the change in biomass is calculated by taking the tree biomass carbon stock of each state at two-time periods during 2006 and 2013. The rate of change of biomass carbon of Meghalaya state is calculated as shown in Table 5.3. Similar method was used for calculation of rate of change of biomass of the remaining four states.

This rate of change in biomass is used to calculate the carbon stock change of settlement areas, other land and agricultural land, since TOF consist of all the non-forest land categories. For a rate of change from forest to agricultural land we used a rate of change of -16.45 t/ha and a value of 16.45 t/ha from agricultural land to forest land as suggested by GHC platform India (Padmanabha 2016). The area of wasteland converted to agricultural land, forest to agricultural land, agricultural land to wasteland, agricultural land to forest and wasteland to settlement areas were obtained using Combine tool and these areas are multiplied by their rate of change to obtain the emission caused from the conversion of these landuse.

5.2.5 Calculation of changes in soil carbon stock

Due to the lack of soil carbon data at two-time periods, the stock difference method that was applied in biomass vegetation cannot be applied for changes in SOC stock. The methodology used for calculation of SOC stock is based on the difference of SOC stock between different landuse categories. Soil carbon stock differ from one landuse to other landuse of a region(Chuai et al., 2014) and when one landuse is converted to another types, its SOC stock tends to be similar to the new landuse(Zhang and Cao, 2015). Based on this concept, the change in SOC stock is calculated as:

$$C_S = (SOC_{AFTERi} - SOC_{BEFOREi}) \times Area_{converted} \tag{5.3}$$

Where C_S is change in soil carbon stock when one landuse is converted to another type, SOC_{AFTERi} is soil carbon stock of landuse i immediately after conversion and $SOC_{BEFOREi}$ is soil carbon stock of a landuse i before it gets converted into a new landuse. $Area_{converted}$ is the area of land where landuse i is converted to a new landuse.

Different methods (mean, median, profile statistic) can be applied to upscale SOC stock (Lai et al., 2016). We used mean method to upscale the SOC stock of the study area. The area of each state is stratified into different landuse and then mean density values of each landuse of a particular state is multiplied with the area of that landuse in that particular state. The mean SOC values of different landuse from each state as shown in Table 5.4 were from the previous objectives and from secondary source obtained from published data base of National Bureau of Soil Survey and Landuse Planning (NBSS and LUP) Nagpur(Bhattacharyya, 2004; Maji, 2004; Vadivelu et al., 2004; Singh and Bengtsson, 2005). Here, we assumed that carbon densities of each landuse remained constant with time.

5.2.6 Calculation of changes in carbon stock from landuse management

Carbon emission related to forest management were calculated for a period of 2005-2010 using country specific data(Table 5.5) obtained from statistical year book of India (www.indiastat.com).

Change of carbon stock was calculated from each state as a result of loss of carbon value due to fuel wood gathering using an empirical model of IPCC:

$$L_{fuelwood} = FG \times D \times BEF \times CF \tag{5.4}$$

Table 5.3: Rate of change of biomass of TOF in Meghalaya

State: Meghalaya	**2006 (SFR 2009)**	**2013 (SFR 2015)**
Growing stock of TOF (Million cumec)	23.47	19.08
Above ground biomass = Growing stock x density(0.7116)x biomass expansion ratio(1.575) (Based on FSI Report, 2009)	26.30	21.38
Below ground biomass = root shoot ratio:0.27 (IPCC 2006)	7.10	5.77
Total biomass(ABG+ BGB)	33.41	27.16
Total carbon biomass (carbon fraction * 0.5)	16.70	13.58
Rate of change of biomass in (t C /ha/yr)	-1.2156	

Where $L_{fuelwood}$ refers to loss in carbon due to fuel wood gathering, FG refers to annual volume of fuel wood gathering (m^3/yr), D refers to basic wood mean density (0.7116)(Brown et al., 1991; Rajput et al., 1996; Kaul et al., 2011), BEF refers to biomass expansion factor(1.575)(FSI, 2009) and CF refers to carbon factor (0.5).

Carbon stock changes as a result of agricultural land and grassland management were also calculated as per the empirical model defined by IPCC. The carbon stock

Table 5.4: Mean SOC stock under different landuse

State	**Mean SOC stock (t/ha)**				
	Settlement	**Agricultural land**	**Other land**	**Forest**	**Grassland**
Assam	16.005	33.08	25.33	40.89	51.87
Manipur	16.004	33.58	25.45	36.68	55.54
Meghalaya	16.005	33.52	25.33	41.01	50.72
Nagaland	16.005	33.76	25.20	40.53	50.95
Tripura	16.004	33.60	24.20	40.86	49.71

change is calculated as:

$$C_s = SOC_{Ref} \times F_{Lu} \times F_{MG} \times F_I \times A \tag{5.5}$$

Where C_s refers to change in SOC stock, SOC_{Ref} refers to SOC value, F_{Lu}, F_{MG}, F_I refers to landuse, land management and fertilizers impact factors respectively, and A refers to area of the landuse. Detailed values of F_{Lu}, F_{MG}, F_I can be found in Table 5.6 and Table 5.7.

Table 5.5: Statewise production of timber in India

State	**2005-2006 (m^3)**	**2006-2007 (m^3)**	**2007-2008 (m^3)**	**2008-2009 (m^3)**	**2009-2010 (m^3)**
Assam	11970	27490	13630	13930	7330
Manipur	9070	9110	8580	2670	6410
Meghalaya	80	980	1020	880	520
Nagaland	25000	25000	25000	25000	25000
Tripura	2100	2100	2100	2100	2100

Table 5.6: SOC stock change factor for cropland management

Factor	**Level**	**Moisture regime**	**Temperate/ Boreal**	**Tropical**	**Tropical Montane**
Landuse (FLu)	Long term cultivated	Dry	0.80	0.58	0.64
		Moist/wet	0.69	0.48	
Tillage (FMG)	Full	Dry	1.00	1.00	1.00
		Moist/wet	1.00	1.00	1.00
	Reduced	Dry	1.02	1.09	1.09
		Moist/wet	1.08	1.15	
	No till	Dry	1.10	1.17	1.16
		Moist/wet	1.15	1.22	
Input (FI)	Low	Dry	0.95	0.95	0.94
		Moist/wet	0.92	0.92	
	High without manure	Dry	1.04	1.04	1.08
		Moist/wet	1.11	1.11	
	High with manure	Dry	1.37	1.37	1.41
		Moist/wet	1.44	1.44	

Table 5.7: SOC stock change factor for grassland management

Factor	**Level**	**Climate regime**	**IPCC value**
Landuse (FLu)	All	All	1.00
Management (FMG)	Nominally managed (non–degraded)	All	1.00
	Moderately degraded grassland	Temperate/Boreal Tropical Tropical Montane	0.95 0.97 0.96
	Severely degraded	All	0.70
	Improved grassland	Temperate / Boreal Tropical Tropical Montane	1.14 1.17 1.16
Input (FI) (applied to improve grassland)	Nominal	All	1.0
	High	All	1.10

Table 5.8: State wise consumption of organic manures and chemical

State	**Organic Manures (MT)**	**Urea (MT)**	**DAP (MT)**	**MOP (MT)**
Assam	916750000	281510	34790	111330
Manipur	61000	17140	2140	1940
Meghalaya	1635000	7200	1080	450
Nagaland	88000	1610	1200	510
Tripura	0	20170	3830	7610

5.3 Result

5.3.1 Landuse/Land cover changes

The landuse/land cover maps obtained from National Remote Sensing Center (NRSC) Hyderabad, through Bhuvan-portal from 2006-2013 were used to analyze the spatial and temporal changes in landuse landcover and change in carbon stock across the five states of Northeast India viz. Assam, Meghalaya, Manipur, Nagaland and Tripura. In 2013, the areas of the six main categories of landuse ordered by areas in Assam were 369.67 x 104 ha (47.13 % of the total area) for agricultural land, 268.87 x 104 ha (34.28%)

for forest, 80.72 x 104 ha (10.29%) for water bodies,41.06 x 104 ha (5.23%) for other land, 12.82 x 104 ha (1.63 %) for settlement and 11.25 x 104 ha (1.43 %) for grassland; in Manipur the landuse in 2013 ordered by areas were 177.45 x 104 ha (79.48 %) for forest, 28.08 x 104 ha (12.58 %) for agricultural land, 8.37 x 104 ha (3.75%) for other land, 5.04 x 104 ha (2.26%) for water bodies, 4.33 x 104 ha (1.94 %) for settlement and 8.25 ha (0.00037 %) for grassland; in Meghalaya the landuse in 2013 ordered by areas were 180.83 x 104 ha (80.62 %) for forest, 22.13 x 104 ha (9.87%) for other land, 14.35 x 104 ha (6.40 %) for agricultural land,5.21 x 104 ha (2.32 %) for settlement, 1.77 x 104 ha (0.79%) for water bodies and 1.77 x 104 ha (0.00013%) for grassland; in Nagaland the landuse in 2013 ordered by areas were 130.32 x 104 ha (78.61 %) for forest,21.84 x 104 ha (13.17 %) for agricultural land, 9.44 x 104 ha (5.69%) for other land,3.05 x 104 ha (1.84%) for settlement, 1.07x 104 ha (0.65%) for water bodies and 0.07 x 104 ha (0.04%) for grassland; in Tripura the landuse in 2013 ordered by areas were 73.84 x 104 ha (70.42 %) for forest, 21.72 x 104 ha (20.72%) for agricultural land, 4.64 x 104 ha (4.43 %) for settlement, 3.71x 104 ha (3.54%) for other land, 0.94 x 104 ha (0.90%) for water bodies and 2.19 ha (0.0002%) for grassland.

These remote sensing landuse data obtained from NRSC between the periods of 2006 to 2013, showed that there is a massive changes of land cover in NE region (Figure. 5.1).Between 2006 and 2013, Assam experienced a net increase in agricultural land by 58.70 x 104 ha (7.48%), increase in settlement area by 5.59 x 104 ha(0.71%) at the expenses of decrease in other land by 62.32 x 104 ha (7.95%),decrease in grassland by 1.34 x 104 ha(0.17%), decrease in water bodies by 0.59 x 104 ha (0.07 %) and decrease in forestland by 0.04 x 104 ha (0.005%); Manipur experienced a net increase in agricultural land by 4.91 x 104 ha (2.20%), increase in settlement area by 1.67 x 104 ha (0.75%) at the expenses of decrease in forestland by 3.93 x 104 ha(1.76 %), decrease in other land by 2.55 x 104 ha (1.14%) and decrease in water bodies by 0.11 x 104 ha(0.05 %); Meghalaya experienced a net increase in settlement areas by 2.13 x 104 ha(0.95%), increase in agricultural land by 1.46 x 104 ha(0.65%) at the expenses of decrease in other land 2.56 x 104 ha(1.14%),decrease in forest by 0.97 x 104 ha(0.43%) and decrease in water bodies by 0.06 x 104 ha(0.03%); Nagaland experienced a net increase in settlement areas by 1.23 x 104 ha(0.74%),increase in other land by 1.10 x 104 ha(0.66%) at the

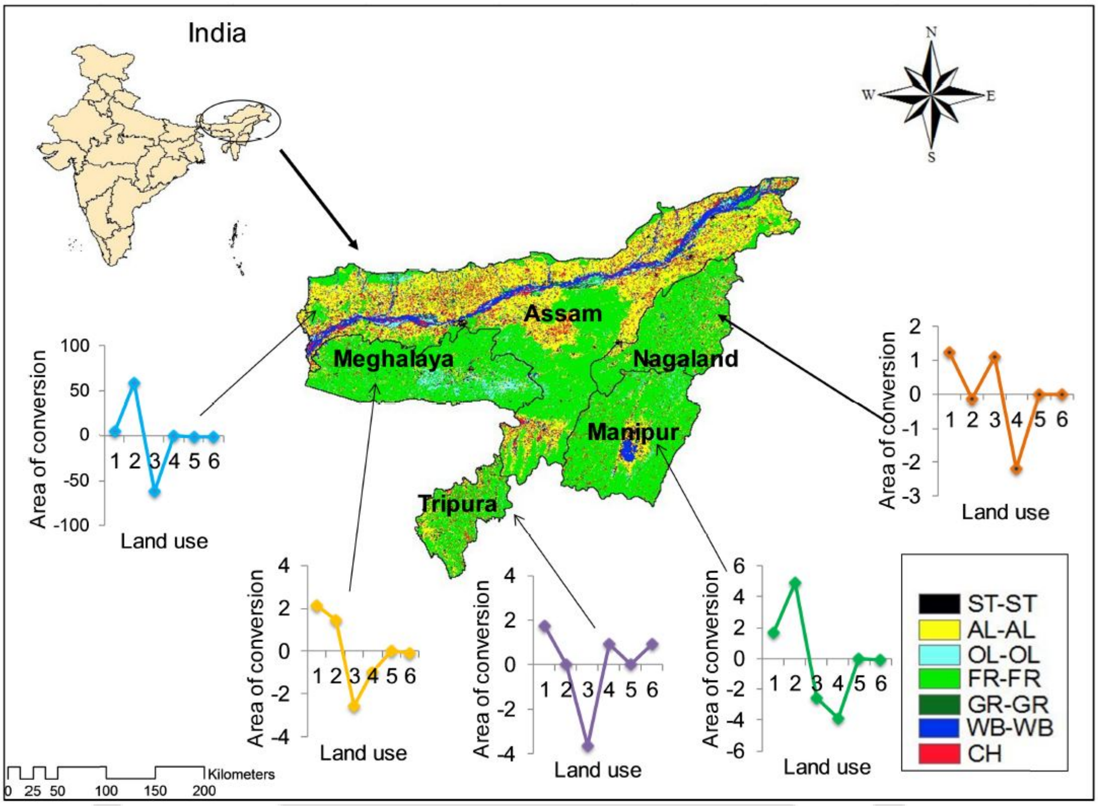


Figure 5.1: Landuse conversion in five states of NE India from 2006-2013 (unit: 10^4 ha): The letter ST-ST, AL-AL, OL-OL, FR-FR, GR-GR and WB-WB represent landuse categories remaining same as settlement, agricultural land, other land, forest land, grassland and water bodies between 2006 to 2013; whereas letter CH indicates areas that have undergone conversion. The numbers 1-6 in line diagram denotes the changes in area (10^4 ha) of settlement, agricultural land, other land, forest, grassland and water bodies.

expenses of decrease in forest area by 2.19 x 104 ha(1.32%) and decrease in cropland by 0.14 x 104 ha(0.08%); Tripura experienced a net increase in settlement areas by 1.74 x 104 ha(1.66%), increase in forest area by 0.94 x 104 ha(0.89%), increase in water bodies by 0.93 x 104 ha(0.89%),increase in agricultural area by 0.04 x 104 ha(0.04%) at the expenses of decrease in other land by 3.65 x 104 ha(3.48%).

5.3.2 Impacts of landuse change on carbon stock

Conversion of landuse between 2006 and 2013 has led to overall decrease of carbon biomass in all the four states of Northeast India except in Tripura. The amount of changes in carbon biomass varies from states to states (Figure 5.2).Assam, Manipur, Meghalaya and Nagaland experienced a net decrease in carbon biomass between these two periods by an amount of approximately 0.43,1.51, 0.31 and 0.49 TgC respectively, whereas Tripura experienced a net accumulation of carbon biomass approximately by 0.12 TgC due to increase of its forest cover between these periods. The amount of change in SOC stock due to landuse conversion between 2006 and 2013 also varies among these five states. Whereas Assam, Manipur and Tripura experienced a net accumulation of SOC stock by an amount of approximately 3.91, 0.22, 0.13TgC, SOC stock declined in Meghalaya and Nagaland approximately by an amount 0.11 and 0.62 TgC.

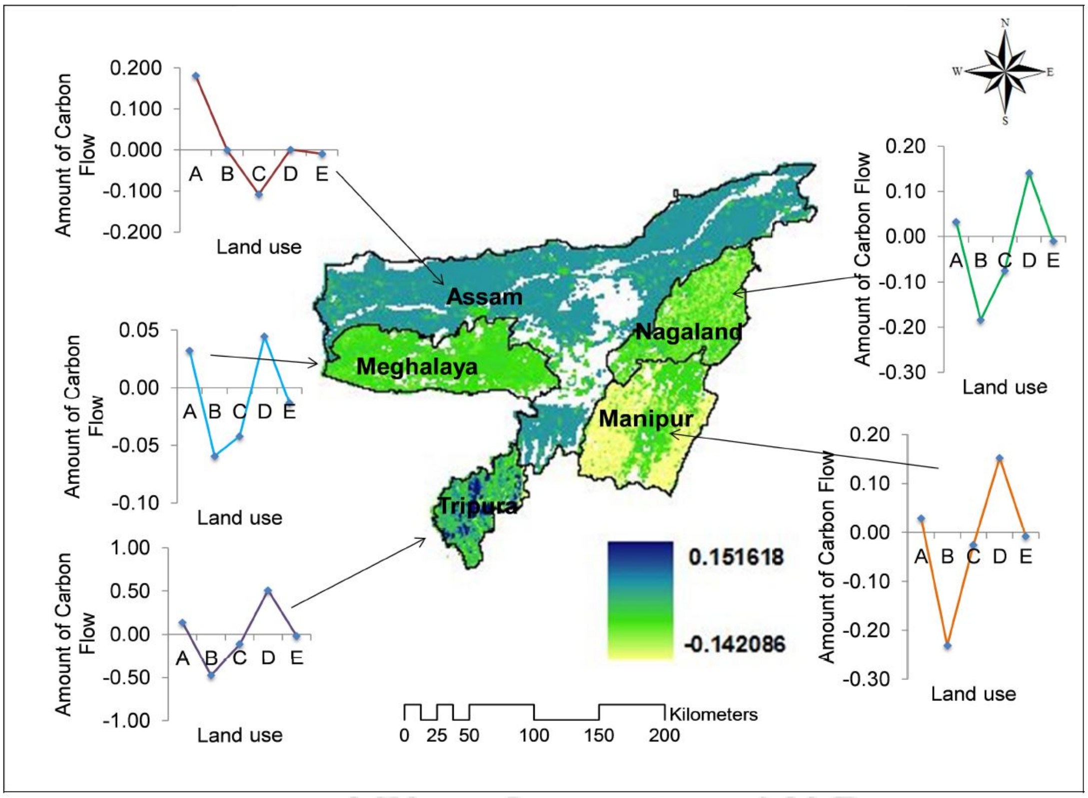


Figure 5.2: Change in total carbon stock due to landuse conversion (Mg C/ha/year): The alphabets A to E in the x-axis of the line diagram indicate conversion of other land to agricultural land, forest to agricultural land, agricultural land to other land, agricultural land to forest and other land to settlement whereas y axis indicates the amount of changes in carbon stock (Mg C/ha/year) from both vegetation and soil because of this conversion.

5.3.3 Impacts of landuse management on carbon stock

Landuse management of forest, cropland and grassland can cause alteration in carbon storage. Forest management includes fertilization, forest regeneration, forest fire control and pest management which can increase forest biomass and carbon stock. However, activities like fuel wood collection, timber harvesting leads to declination of forest biomass and ultimately reduce the forest carbon stock.

Here we estimated change of carbon stock from each state as a result of fuel wood gathering using an empirical model of IPCC and data(Table 5.5)obtained from statistical year book of India. The total biomass loss as a result of fuel wood gathering in Assam, Manipur, Meghalaya, Nagaland and Tripura were approximately 0.0083, 0.0040, 0.00039, 0.014, 0.0011 TgCyear^{-1}.

There is a regional difference in the amount of changes in carbon stock due to agricultural management. Agricultural management in Assam, Manipur, Meghalaya and Nagaland resulted in accumulation of SOC approximately 15.08, 1.03, 0.56, 0.025 TgCyear^{-1} whereas Tripura resulted in declination of SOC of approximately by 0.66 TgCyear^{-1}due to poor management of tillage and fertilizers application (Figure 5.3).For grassland management, moderately degraded grassland as per IPCC was assumed for the all the states. Hence declination of carbon storage due to grassland management in Assam, Manipur, Meghalaya, Nagaland and Tripura were approximately 0.80, 2.84 x 10-5, 9.06 x 10-6, 0.002 and 2.9 x 10-6 TgC /year.

5.3.4 Carbon stock due to the combined effect of LULC and landuse management

The combined effect of landuse conversion and landuse management viz. cropland management, grassland management and forest management (fuel food gathering) leads to carbon accumulation of 14.76 TgC/year in Assam, 0.84TgC/year in Manipur and 0.48 TgC/year in Meghalaya whereas Nagaland and Tripura experienced a carbon loss of -0.14 and -0.62 TgC/year. Conversion of cropland into forest land and other land into cropland leads to an increase of SOC values while conversion of forest into agricultural

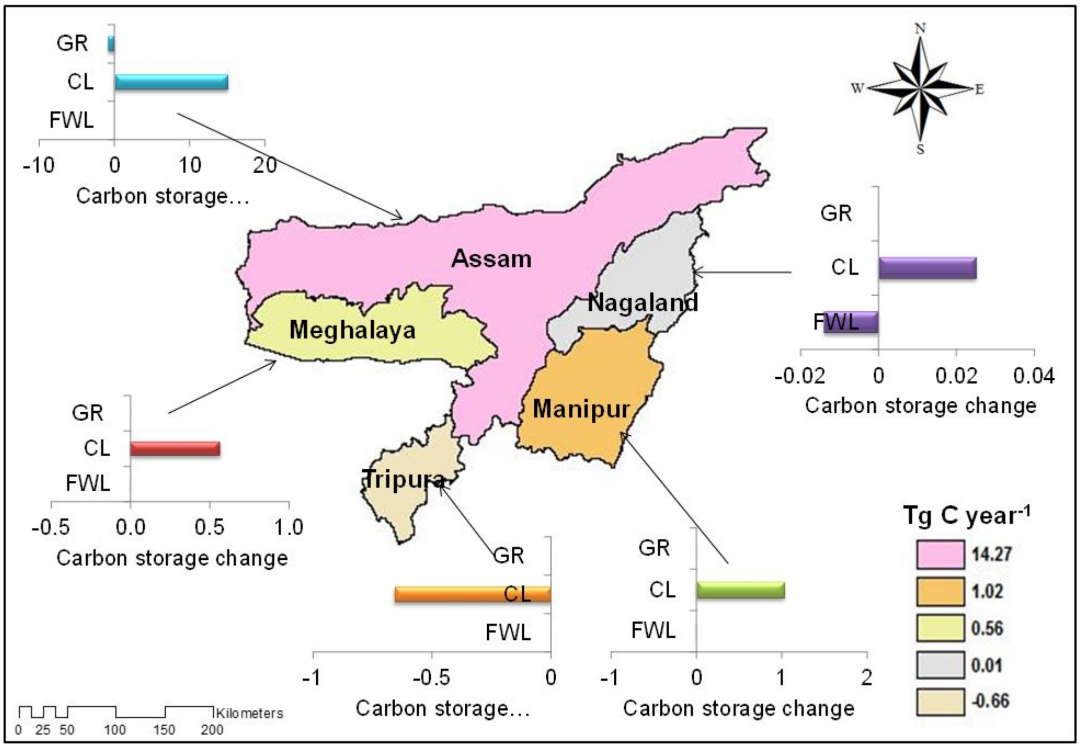


Figure 5.3: Total carbon storage changes due to landuse management (TgC/year): The letter GR, CL and FWL in the bar diagram represent grassland, cropland and fuel wood gathering respectively.

land, conversion of cropland into other land and conversion of other land into settlement leads to carbon emission. Fuel wood gathering and grassland management causes carbon emission while use of organic manures and proper drainage of cropland leads to carbon accumulation.

5.4 Discussion

Landuse landcover conversion has a great influence on the amount of carbon storage and carbon emission(Houghton et al., 2012). Intergovernmental Panel on Climate Change (IPCC) has developed many empirical models and provides policies and guidelines to quantify and control carbon (Nakienovi and Swart, 2000; IPCC, 2006; Metz et al., 2005). However regional studies on carbon emission related to landuse landcover changes especially in NE India are still limited. To our knowledge, this is the first estimate of carbon emission from landuse changes and landuse management in Northeast

India. In this study, we calculated the carbon emission from vegetation and soil due to conversion between various landuse except when a landuse is converted to a water bodies or a water bodies is converted into other landuse due to lack of available information about carbon storage stored in water bodies. Furthermore, most of the studies related to change in vegetation carbon(Lai et al., 2016; Zhang and Cao, 2015) are literature based on the estimation which was obtained from the past few years or from a similar region. However in reality the vegetation carbon changes with CO_2 fertilization, pollution and climate change(Houghton et al., 2012).In this study, the carbon densities of vegetation are not from the past studies but of those same particular years i.e. of 2006 and 2013 where the analysis was carried out and the data for analysis were obtained from Forest report of India (FSI, 2009, 2015) . Result from this study indicated that landuse conversion can have a great influence on carbon storage of both the vegetation and soil of NE India. However, the amount of changes in carbon storage varies from soil and vegetation and also from state to state. The total biomass from both trees outside forest (TOF) and forest areas in Assam, Manipur, Meghalaya and Nagaland were found to decline at the rate of approximately -0.06, -0.21, -0.04, -0.07 TgC/year. The main reason for declination of biomass in NE India is due to biotic pressure and shifting cultivation(FSI, 2013) . Shifting cultivation is the main reason that leads to the declination of most of the forest cover in NE India particularly Meghalaya, Manipur and Nagaland(Murthy et al., 2013). In Assam apart from shifting cultivation, rapid urbanization and other factors are responsible for declination of forest cover(Ranjan and Upadhyay, 1999). However, in Tripura the total biomass from both TOF and forest area was found to increase by 0.01TgC/year mainly due to the increase of forest cover between 2006 and 2013. The reason in increase of forest cover may be attributed to the various jhum and jhumia rehabilitation schemes implement by the government and Maharaja(prince) of Tripura to check shifting cultivation and to regenerate forest in shifting cultivation affected areas (Das and Das, 2014).Jhum here refers to the agricultural system also known as shifting cultivation which is commonly practice in NE India. In such agricultural system, the trees and vegetation are cleared and burns before the crops are sown, so that they will act as manure for the crop. Jhumia here refers to the people who practices jhum cultivation. Various Jhum and jhumia scheme have been implemented in Tripura by declaring more and more forest areas as reserved forest and preventing the jhumia their rights to practice jhum cultivation. In doing so, it leads to the increase of forest cover and increase in the net revenue earned by the government and Maharaja from the forest cover(Dasgupta, 2017).National Forest Policy 1952 (NFP 1952) ,National Forest Policy 1988 (NFP 1988) and recently Forest Right Act 2006 (FRA 2006) have been implemented in Tripura to check and reduce shifting cultivation. Although, currently shifting cultivation is still prevailing in some part of Tripura(Das and Das, 2014), however its extent is less compared to other northeast state(Maithani, 2005)

Between the periods of 2006 to 2013, SOC stock in Assam, Manipur and Tripura were found to increase by an amount of approximately 0.55, 0.03 and 0.01 TgC/year. The main reason of this increase may be attributed to the large conversion of other land into agricultural land in Assam and Manipur, however in Tripura it may be attributed to the increase in forest cover. Whereas Meghalaya and Nagaland experienced a net decrease in SOC stock approximately by an amount of -0.01 and -0.08 TgC/year. This decline in SOC stock may be attributed to the decline in forest cover and conversion of agricultural land into other land during this period.

This study also made an attempt to study carbon emission due to landuse management. Result indicated that timber harvesting leads to carbon emission of approximately 0.0083, 0.0040, 0.00039, 0.014, 0.0011 TgCyear^{-1}in Assam, Manipur, Meghalaya, Nagaland and Tripura respectively. As shown in Table 5.8, the data obtained from statistical year book of India showed that in Assam, Manipur, Meghalaya and Nagaland the farmers have started to do away with chemical fertilizers like urea, DAP, MOP and slowly shift towards organic fertilizers. Application of organic fertilizers will lead to higher accumulation of soil C and N than chemical fertilizers(Dou et al., 2016). Hence these four states experienced an increase in SOC content due to their proper field management, whereas Tripura uses lots of chemical fertilizers leading to decrease in SOC due to poor management. As for grassland management we assumed that the grassland is degraded with time in these states leading to loss of carbon. There is no proper sound management of grassland in India, with grassland ecosystem being the most neglected ecosystem by the ministry of Environment and Forest in India(Singh et al., 2006) . Grassland being one of the ecosystem that can store huge amount of carbon(Lai et al., 2016), the government must give greater importance to protect and improve the grassland of NE India for environmental protection and improving the livestock and economy of the people.

Although this study provides an insight of how landuse conversion and landuse management can affect the amount of carbon flux in NE India, the results of this study must be read carefully as there are limitations within the study. In this study, for cropland and grassland management we used a default value defined by IPCC value (Tanabe and Wagner, 2003), however these values may be different for a region like NE India. Here, due to the lack of soil carbon data at two-time periods, we assumed that carbon densities of each landuse remained constant with time. This may lead to over or under estimate of carbon values, as carbons values of each landuse do actually vary with time as a result of changing climate and various management factors. Our study also did not cover changes due to conversion of landuse into water bodies and vice versa due to data limitation; however, this is another important landuse that must be taken into consideration. Our period of study is 8 years which is sufficient enough for that landuse to reach a carbon level to which it is converted, however carbon in soil may require longer period to be stabilized (Chuai et al., 2013). Hence the carbon changes in this work may be called as potential changes rather than actual changes.

As more changes in landuse are expected to occur in NE India in the coming decades, more research is needed to improve measurement of carbon emission from various landuse types, from various ecosystems and at various scales. To improve the uncertainties involves in monitoring of SOC changes, direct and continuous measurements of SOC are needed. Higher resolution (both spatially and temporal) LULC data are required to effectively monitor changes of various landuse. With inclusion of the above-mentioned data and accounting for various sources and uncertainties associated with the analysis, the method proposed by IPCC that was used in this study can be applied for other regions worldwide and can serve as a tool to monitor carbon emission from landuse changes.

5.5 Conclusion

Northeast India has experienced an enormous change in its landuse in recent decades, which are driven by its unparalleled economic development and population growth. We analyzed changes of landuse type conversion and land management in NE India from carbon storage perspective. Our results provide an insight of how landuse and land management can cause a large amount of carbon fluxes in NE India. We found that landuse conversion and land management in NE India are moving towards the opposite direction of carbon reduction. The main reasons can be attributed to the decrease in forest land to meet the demand for carbon absorption, improper grassland and agricultural land management and rapid expansion of settlement areas. With more changes in landuse expected to occur in the future and landuse are often neglected in the landuse land management planning, our results stress that the government and landuse planner of this region must include carbon emission in their future landuse planning to help in mitigation of carbon emission and to slow down the changing climate in the coming decades.

CHAPTER 6

Framework for Soil quality assessment

6.1 Introduction

In this chapter, a soil quality index was developed to assess the effect of various agricultural managements that are currently practiced in Northeast India (NE) on selected physical, chemical and biological soil properties. Previous chapter provide an insight of how landuse and land management can cause a large amount of carbon fluxes in NE India. Therefore to make a sound decision in selection of suitable landuse and land management, understanding of how soils respond to different landuse and management scenarios is essential.

Soil together with air and water are the world most important natural resources. Soil quality is described as “the ability of a soil to adequately function under a particular ecosystem and boundaries of a land cover, to maintain various biological productivity, sustain the environmental quality and enhance animals and plants health”(Doran and Parkin, 1994). Thus from the definition, it’s clearly denotes soil quality as a crucial determinant of environmental sustainability and agricultural productivity; the two most essential difficulties confronting the present reality.

Under natural condition, soils maintain its quality and its equilibrium through pedogenetic processes (Carter, 2002). However, human activities such as drastic change in landuse and soil management (LUSM), deforestation, mining, overgrazing as a way to meet the demand for growing populations, has led to the deterioration of soil and environmental quality (Blanco-Canqui and Lal, 2010; Nabiollahi et al., 2018). Hence, in order to make a decision on the sustainability of landuse and soil managements system predominant in a region, understanding of how soils respond to different landuse and management scenarios on regional scale is essential.

To evaluate the effectiveness of particular LUSM system, single individual soil property such as soil organic carbon, may not be sufficient to come to a conclusion, hence a concept of soil quality index (SQI) by integrating various soil parameters could provide us a better result in interpreting the quality of a soil (Mukherjee and Lal, 2014). SQI is an effective comprehensible method for determining whether the quality of a soil is declining, improving or remain stable under various landuse and soil management (Masto et al., 2008). It also enables comparison of soil quality between field of different landuse and management (Gelaw et al., 2015). Such information can give early cautioning indications of unfavorable trends of various managements, detect the problem areas and can serve as a base whereupon ensuing and future assessment can be assessed (Şeker et al., 2017). It can also provide important information for decision makers and landuse planner to make acquainted decisions against soil quality degradation(Chen et al., 2017).

Although numerous studies on the effect of LUSM on soil quality have been carried out in various regions of the world, including in India (Masto et al., 2007; Ayoubi et al., 2011), however such study are still rather very meagre and scanty in Northeast India, which has recently observed a drastic changes in landuse(Behera et al., 2016).

Major part of North East India were initially covered with forest cover, however due to pressure of rapid growing population, forest areas are now being progressively cleared to be put under various landuse with extensive agricultural practices such as shifting cultivation (Deb et al., 2013). Shifting cultivation has been reported by researchers to result in soil loss and degradation (Singh et al., 2014; Mishra et al., 2017). Bun cultivation on hill slopes and valleys is another settled traditional agricultural system practiced in North East India. This practice also brought diverse opinion on its effectiveness in the long term. Some see it as an efficient system while others consider it as diversified system together with conservation of rich cultural heritage of plants. Pinus kesiya, is another types of forest cover that is found abundant in North East India particularly in region like Meghalaya. Little research has been done on the effect of this type of trees on soil properties (Tripathi et al., 2004).

Sustainability of agricultural system in NE India is an important issue. Thus the evaluation and change in direction with time is an important indicator whether different landuse and management practices are sustainable. A soil quality index can help to assess the soil quality of a site/landuse and enable the comparison between different LUSM types. Also identification of the important defining soil quality parameters under the predominant landuse type is pivotal for developing measures to enhance soil quality and productivity in the future. Since such investigations have not been studied in the region until now, goal of the present objective is to find out the suitable soil quality indicators and to access the soil quality (using Soil quality index) of the five prevalent landuse system in NE India.

6.2 Materials and Method

6.2.1 Selection of Landuse and Soil Management Systems

Five landuse and soil management systems (LUSM) were selected based on the following three steps. In the first step details about the past and current LUSM were obtained and described. Sites for soil sampling were then identified for each LUSM. In the final step, soil samples from the identified sites were collected, stored and analysed in the laboratory for various soil indicators.

In the first step, field reconnaissance survey, enquiry and discussion with the local farmers who are well acquaintance with the landuse and local farming systems were conducted. Based on the obtained information, five predominant LUSM (Figure 6.1) were chosen and are described (Table 6.1). Terrain characteristics and vegetation types from each LUSM were also recorded during sampling. The five LUSM selected for evaluation of soil quality were: 1) dense forest 2) pine forest 3) terrace/bun agricultural system 4) shifting/jhum cultivation and 4) abandoned land after shifting cultivation.

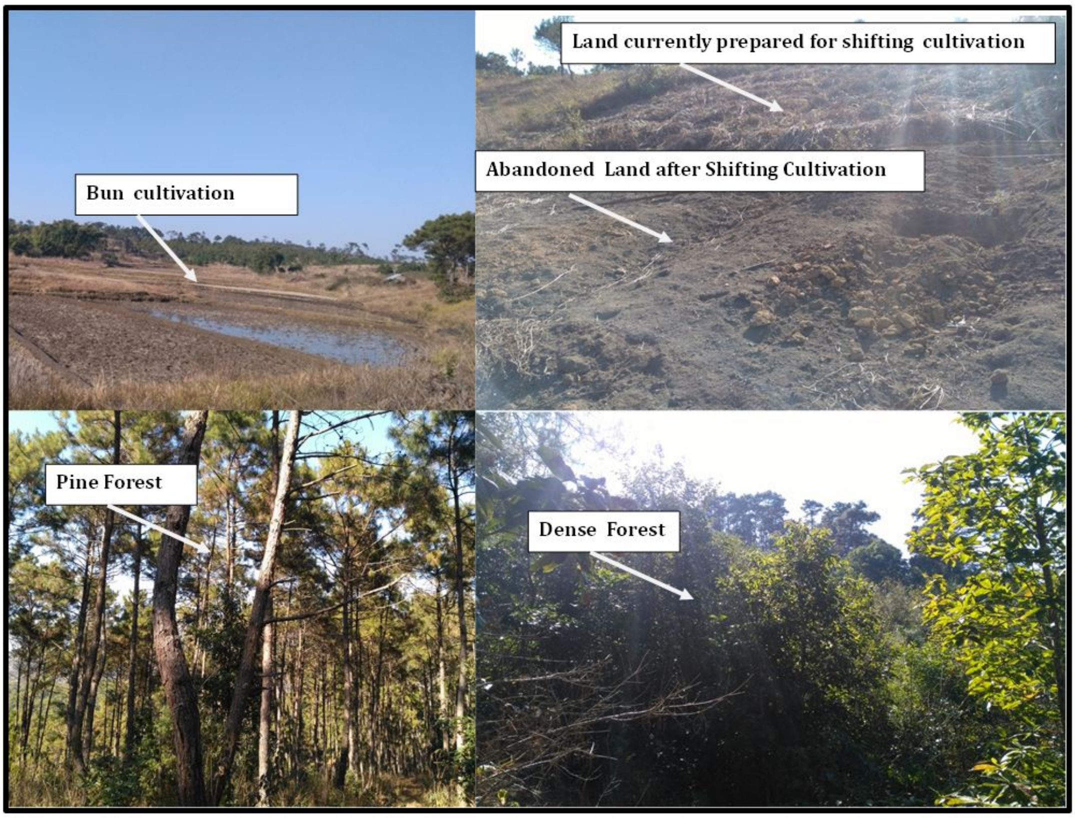


Figure 6.1: Five landuse and soil management system (LUSM) considered in the study (Photos taken during sampling. Description can be found in Table 6.1

6.2.2 Soil sampling

Similar to the previous objectives, all the soil samples were air-dried, sieve through 2 mm sieves, and stored for further analysis of soil quality indicators. The soil samples were then carried out to the lab and analyse for selected soil quality indicators.

6.3 Physical, chemical and Biological Analysis

6.3.1 Determination of soil pH

Determination of pH is carried out to measure the hydrogen ion concentration in the soil-water system. The pH value indicates whether the soil is alkaline, acidic or neutral and gives us an idea about the nutrients availability for plants. Nutrients availability is maximum at neutral pH and decreases with increasing in alkalinity and acidity.

Table 6.1: Description of landuse and soil management system selected for the study

Sr. No	**Landuse and Soil Management Systems**	**Description**
1.	Dense forest	Less disturbed, having rare species of orchids and support varieties of native trees and vegetation.
2	Pine Forest	These forests are mostly disturbed and fragmented. Shifting cultivation is commonly practice along the forest. It supports a variety of plant communities ranging from weed to grassland on repeatedly burnt sites.
3	Terrace/ bun Cultivation	Terrace like steps were created on the sides of a mountains or on valleys. Various crops are grown on each of these steps. The main aim of this practice is to reduce the water velocity, thus help to preserve water and soil nutrients.
4	Shifting Cultivation	Vegetation and trees are slashed down, left dry and are burnt in situ. The rain washes the fresh ashes into the soils, thus providing the necessary nutrients to the soil. After cultivation, the land is abandoned and the farmers shift to next adjacent land and carried out the same process.
5	Abandoned Jhum land	Land abandoned after shifting cultivation.

The pH is determined using 1:2 soil to water ratio. For the analysis 20 grams of soil was mixed with 40 ml distilled water in a 100ml beaker. The suspension was then vigorously shake on a mechanical shaker for 30 minutes. The pH was then determined by immersing the electrodes in a suspension.

pH interpretation:

<5.0 : strongly acidic

5.1 – 6.5 : slightly acidic

6.6 – 7.5 : Neutral

7.6 – 8.0 : Mild alkaline

>8.0 : Highly alkaline.

6.3.2 Determination of soil electrical conductivity

Determination of electrical conductivity (EC) is carried out to measure the amount of total soluble salts present in the soil samples. It is important for monitoring crop nutrients requirement. For example, higher EC value means that there is no need for further fertilization, however if it is too high, then flushing with water may be needed.

For determination of EC, the same procedure as that in soil pH was followed. However, here the suspension was filtered using Whitman papers and EC was measured using conductivity meter.

EC interpretation in term of ds m^{-1} :

<1.0 : No deleterious effect on crops

1 – 2 : critical for slat sensitive crops

2 – 3 : critical for salt tolerant crops

>3.0 : Injurious for crops

Determination of EC gives us an idea about the total salt content presents but it does not differentiate among different individual nutrients (phosphorous, nitrogen etc.). Hence determination for all the other individual nutrients was carried out.

6.3.3 Determination of total nitrogen in soil

Total nitrogen represents the amount of nitrogen presents in both organic and inorganic forms. It is however not the measure of available nitrogen for plants nutrients, it is just an indicator of the soil potential for the element. For the analysis total nitrogen of the soil samples was estimated using Kjeldahl method as suggested by (Horwitz, 1975).

Kjeldahl method for determination of total nitrogen consists of three steps:

1. Digestion
2. Distillation and
3. Titration

Digestion: Digestion of the soil sample is carried out by heating 1g of the soil samples with 10ml of concentrated H_2SO_4 in the presence of copper as a catalyst and K_2SO_4 as a salt to raise the digestion temperature. During this process, the organic substance is being decomposed to liberate the reduced nitrogen as ammonium sulphate. The sample turns light green colour or colourless at the end of this process.
Distillation: The digested samples is then distilled with the help of sodium hydroxide, which finally convert the ammonium salt into ammonia.
Titration: The amount of ammonia and nitrogen present in the soil sample is then determined using back titration method.
Simultaneously blank samples without soil is also to be run.
Calculations: Nitrogen content (%) present in the soil=

$$\frac{\text{(Sample reading-Blank reading)} \times \text{Normality of Acid} \times \text{Atomic weight of Nitrogen} \times 100}{\text{Sample weight (in g} \times 1000} \tag{6.1}$$

$$= \frac{\text{(Sample reading-Blank reading)} \times 0.1 \times 14 \times 100}{1 \times 1000} \tag{6.2}$$

Nitrogen content (%) present in the soil = (sample reading-Blank reading) $\times$ 0.14

6.3.4 Determination of Soil Organic Carbon (SOC)

Soil organic carbon (SOC) was determined using Walkley and Black (1934) as described in the first objective.

6.3.5 Determination of soil bulk density

Bulk density is the ratio of the mass of oven dried soil to its bulk volume at the time of sampling (i.e. solid and pore space). For determination of bulk density core method was used (Black et al., 1965). To do so, the core cylinder is driven into the soil up to desired soil depth with blows from a hammer. The core which contains undisturbed soil sample is then removed carefully and trimmed at the end to get a core sample whose volume can be determined knowing its depth and diameter. The weight of this soil core is also determined before and after dying in an oven at 105°for 24 hours.

$$\text{Bulk density (g/cm}^3\text{)} = \frac{\text{Dry soil weight (g)}}{\text{Soil volume (cm}^3\text{)}} \tag{6.3}$$

6.3.6 Determination of soil porosity

Porosity refers to the volume of soil samples which is occupied by air and water. This soil property need not to be calculated directly as it can be calculated using bulk density and particle density.

$$\text{Porosity} = \frac{\text{Bulk Density}}{\text{Particle denisty}} \times 100 \tag{6.4}$$

6.3.7 Determination of phosphorus

Phosphorous is an essential nutrients for the plants and it occurs in many form. There are many method for determination of available phosphorous, here a method proposed by (Olsen, 1954) was used. For the analysis, phosphorous is extracted from the soil sample using 0.5 M of $NAHCO_3$ adjusted to a pH of 8.5. The phosphate ion in solution is then treated with ascorbic acid in acidic medium. This will create a blue colour in the solution which is then read using a colorimeter. Based on this colour the available phosphorous is calculated. The reagents used for the analysis are (a) 0.5 M of sodium bicarbonate solution (prepared by adding 42g of $NAHCO_3$ with distilled water and adjust the solution to 8.5 pH) (b) activated charcoal (c) 5N sulphuric acid (prepared by adding 141 ml of con H_2SO_4 to 800 ml of distilled water, cool it down and dilute up to 1L of distilled water) (d) ammonium molybdate solution (e) ascorbic acid solution (f) standard phosphate solution. Before calculation, the standard curve was also prepared as per the procedure prescribed by Olsen.

Calculation:

Weight of the soil =2.5 g

Volume of $NAHCO_3$ extract = 50ml

Volume of extract used for colour development =10ml

Let reading from colorimeter/spectrophotometer =y

If concentration of phosphorous read from standard curve (this is the concentration present in 10ml of aliquot) = C μ g mL^{-1}

Therefore for 1ml, concentration of phosphorous = C/10μ g mL−1

Concentration of phosphorous in 50 ml extract (from 2.5 g of soil) = $C/10 \times 50\mu$ gmL^{-1}

For 1g of soil, Concentration of phosphorous= $C/10 \times 50/2.5\mu$ gmL^{-1}

Therefore available P (Kg ha^{-1}) = $C/10 \times 50/2.5 \times 2.24$ [2.24 is conversion from ppm] = C×4.48

6.3.8 Determination of Available nitrogen in soil

For the analysis 5 g of soil was taken and mixed with 20 ml distilled water. The solution is further added with 50 ml 0.32% of $KMNO_4$, 50 ml of 2.5% NaOH and 1-2 g paraffin wax. In the process, the organic matter existing in the soil is being oxidized by nascent oxygen which is liberated by $KMNO_4$ in the presence of NaOH and ammonia is released. This volume of ammonia is absorbed in a known volume of standard acid 20 ml 2% boric acid and is determined by titration with 0.02 N H_2SO_4 (David, 1960)

Calculation:

Mineralizable or Available N (Kg ha^{-1})=

$$\frac{R \times 0.02 \times 0.014}{W.S \times 2.24 \times 10^6} \tag{6.5}$$

Where, R is the Volume of 0.02 N H_2SO_4, W.S refer to weight of sample

6.3.9 Determination of exchangeable potassium

Available potassium (K) represents the exchangeable and water soluble potassium. The determination of available potassium was carried out using flame photometer (David, 1960). The reagents used for the analysis are (a) Neutral normal ammonium acetate (NH_4OAc) prepared by dissolving 77 g NH_4OAc in distilled water and volume makeup was done up to 1 L, (b) Standard potassium solution prepared by dissolving 1.9066g of dried KCl at 110°C in 1000 mL deionised water to get strength of 1000 mgL^{-1} . The calibration curve was made by preparing standards of 0, 5, 10, 15, 20, 25 and 30 ppm of potassium from 1000 ppm K using NH_4OAc. For the analysis part 10 gm soil solution was taken in 250 ml conical flask. Further, 100 ml of NH_4OAc (pH=7) solution was added. The solution was then shake for 30 minutes and filtered through Whatman filter paper. The extract solution is then used for measuring of available potassium using photometer.

Calculation:

Available K (Kg ha^{-1})=A×V/W×2.24

$$\begin{aligned} \text{Where,} A &= \text{Concentration of K as read from standard curve} \\ V &= \text{Volume of extractant} \\ W &= \text{Weight of the sample} \end{aligned}$$

6.4 Soil quality indexing

Different methods for calculation of soil quality indices were reported in the literatures (Andrews et al., 2002; Rashidi et al., 2010; Gelaw et al., 2015). For the present study, weighted soil quality index was calculated. Irrespective of various methods available, soil quality index computation follows the same three essential steps: indicator selection, indicator transformation/ scoring function and combination of the indicators into one index value (Tesfahunegn, 2014). The detailed description of each steps is explained below.

6.4.1 Indicator selection

Soil parameters for quality indicators were selected based on their ability to describe various soil processes, the ease and minimum cost of sampling and analysis, the sensitivity to management practices and their importance on improving the productivity and preservation of environment degradation as reported in the literatures (Larson and Pierce, 1994; Doran and Parkin, 1994). From a set of original untransformed data, principal component analysis (PCA) and factor analysis were applied to select minimum data sets for defining the soil quality index of various landuse (see statistical method section).

6.4.2 Indicator transformation/ scoring function

The next step is transformation of each indicator and assigning them a score. Depending on their role in soil functioning, each indicator was first classified into ascending order (for 'more is better' function) and descending order (for 'less is better' function). Optimum function was defined for soil attributes such as pH. Each indicator was then transformed into common range between 0 and 1 as per equation 6.1 and 6.2 respectively.

$$Y = \frac{X - a}{b - a} \tag{6.6}$$

$$Z = \frac{b - X}{b - a} \tag{6.7}$$

Where Y and Z are values of each variables after transformation. X is value of the soil attributes to be transform, a and b refers to the minimum and maximum values of each soil attributes. Equation 6.6 is for 'more is better' function and Equation 6.7 for 'less is better' soil function and the combination of both equation is used for optimum function.

6.4.3 Soil quality indexing

Each retained indicator is then weighted based on PCA results. Each Principal component (PC) explained a certain portion of variation in the data set; this percentage divided by the summation of percentage explained by all the PCs with eigenvalues values greater than 1 gives the weighted factor (W) to each soil attributes under a particular

PC. For each observation, the weighted variables' scores were then summed up using Equation 6.8.

$$\text{SQI} = \sum_{i=1}^{n} W_i \times S_i \tag{6.8}$$

Where SQI refers to weighted soil quality index, n to the number of indicators retained, W_i to the weighted PC and S_i to the score of each indicator.

6.5 Statistical Method used for Analysis

- Principal Components Analysis and Varimax Rotation to select minimum data sets for defining the soil quality index.
- Analysis of variance (ANOVA) to evaluate the significant differences of soil quality among different landuse.

6.5.1 Principal Component Analysis

Principal component analysis (PCA) is a statistical technique used for data reduction. Using this technique, a number of possibly correlated variables can be transform into a smaller number of linearly uncorrelated variables called principal components while preserving most of the information of the original variables. Although PCA is a complex mathematical procedure, it can be defined as:

$$PC_1 = a_{11}X_1 + a_{12}X_2 + \dots\dots\dots\dots\dots\dots a_{1k}X_k \tag{6.9}$$

$$PC_2 = a_{21}X_1 + a_{22}X_2 + \dots\dots\dots\dots\dots\dots a_{2k}X_k \tag{6.10}$$

$$\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \tag{6.11}$$

$$PC_k = a_{k1}X_1 + a_{k2}X_2 + \dots\dots\dots\dots\dots\dots a_{kk}X_k \tag{6.12}$$

Where, PCs are principal component and also known as eigenvectors. a_{11}, a_{12}, a_{1k} are coefficient of principal component and are calculated in such a way that the first principal component will account for most of the total data variation, the second principal component will explain the second largest variation and so on. Thus PCA tries to explain majority of the variance in data set with fewest number of components.

Before performing PCA, if all variables are not in the same unit, the variables should be standardized such that:

$$Z_j = \frac{(X_j - \bar{X}_j)}{S_j} \tag{6.13}$$

Where Z_j refer to the score after transformation for j^{th} variable, X_j is the observed variable, $\bar{X}_j$ and S_j refers to the mean and standard deviation of the j^{th} observed variables.

Steps in Conducting Principal Component Analysis

Principal component analysis is carried out in a sequence of steps. These are define below:

Step 1: Initial Extraction of the Components

In PCA method, the number of variables extracted is equivalent to the number of variable being used in the analysis. The first principal component extracted is expected to explain a majority of variance, then each successive component will progressively explained smaller amount of variance. Thus even though a large number of components are extracted, only a few is sufficient to be retained for analysis.

Step 2: Deciding the number of "Meaningful" Components to Retain

A. The eigenvalue-one criterion.

One of the most commonly used criteria for deciding the number of components to be retain in PCA is the eigenvalue-one criterion. Here any components which has eigenvalue values greater than 1 are being retained for the analysis. The reasons for this is straightforward. Each variables adds one unit of variance to the total variance in the data. Therefore any component which is having eigenvalues greater than 1 implies that it can explain a greater amount of variance than that had been explain by one variables. Such component is therefore accounted and retained for analysis.

B. The Scree Plot

Here the eigenvalues of each components is plotted and search for a break between high eigenvalues and low eigenvalues. Those components that appear before the break are considered to be significant and are held for the analysis.

C. Proportion of variance accounted for

Another criteria for deciding the number of components is based on the proportion of variance that the component is accounted for. Then one may one decide to retain the component that account for at least 5 or 10 % of the total variance.

Proportion = Eigenvalue for the component of interest /Total eigenvalues of the correlation matrix.

Step 3: Rotation of the final result

Rotation are performed for the sake of easy interpretation of the extracted components. When more than one PC components has been retained, it is difficult to interpret what construct does component 1, 2 and so on measures. To make interpretation of the results easier, rotation analysis was performed.

Here Varimax rotation was carried out. This rotation is an orthogonal rotation and unlike other rotation, varimax rotation tend to maximize the loadings of each factor. Since our objective is to obtain a variable which load highly on one factor and not the other, therefore this rotation method was chosen for the analysis.

Step 4: Interpreting the rotated solution

This step involve analysing what does the rotated solution represents. This is done by identifying the variable with high loading components.

6.5.2 Analysis of variance (ANOVA)

ANOVA was introduced by Fisher (1925). Even though it is called as analysis of variance, however the purpose of ANOVA is to evaluate whether there exist a significance difference between the means of two or more groups. The null hypothesis in ANOVA is that the means of all the groups is considered are equivalent. It is expressed as:

$$\mu_1 = \mu_2 = \mu_3 = ... = \mu_n \tag{6.14}$$

Where $\mu_1 \mu_2 \ldots \mu_n$ represents the mean of the first, second and n^{th} group respectively. The alternative hypothesis is that the mean of all the group are not equal. It is expressed as:

$$\mu_1 \neq \mu_2 \neq \mu_3 \neq .... \neq \mu_n \tag{6.15}$$

ANOVA uses F-tests to statistically test the null hypothesis. F ratio or F-statistic is defined as:

$$\text{F} = \frac{\text{variation between group}}{\text{variation within group}} \tag{6.16}$$

This F ratio is then compared with the critical value obtained from the probability distribution (i.e. if we choose P <0.05, then this is the value in the f distribution above which 5% of the area under the curve lies). If the F-ratio is greater than the critical value, then the null hypothesis is rejected. The critical value is never less than 1, that means an F-ratio of 1 or less than 1 indicates a non-significant between the groups. If the F-test is found to be statistically significant, then this indicate that there is at least one significant difference in mean. Post hoc test is then used to specific compare the means between each group or in other words to evaluate which specific means are different.

6.6 Results and Discussion

6.6.1 Soil properties

The various soil physical and chemical properties of the selected study area are shown in Table 6.2. Studied soil samples varied from acidic (pH 5-6) to strongly acidic (pH 4-5). Soils under bun cultivation and shifting cultivation have higher soil pH. However, pH of bun cultivation showed considerable variation across different sites. The increase in soil pH in shifting cultivation may be due to liming effect of burning ashes. However, least pH was observed in areas left abandoned after shifting. This may be due to leaching effect of these ashes with time. Even the soils of forest area on higher elevation were found to be strongly acidic because of intense leaching due to heavy rainfall. The organic carbon content was observed between 1.03 to 3.46 %, where all the sites are characterized by higher carbon content. Higher values of SOC were observed in higher elevation compared to lower elevation. A positive correlation between organic carbon and elevation was also observed by other researchers (López-Vicente et al., 2009; Brevik, 2012). In shifting cultivation, although burning of leaves and trunk of trees often volatizes most of the nutrients like nitrogen, carbon and sulphur that are present in the vegetation (Wallenfang et al., 2015), however in this study it was found to have no effect on soil organic carbon. Organic carbon content, total nitrogen and available nitrogen were observed to be higher in area under shifting cultivation. Mean SOC of area under shifting cultivation was even found to be higher than other LUSM except for dense forest. This may be due to incomplete combustion of vegetation which ultimately leads to short-term increase in nutrient availability of the soil. Abandoned soil after shifting were observed to have the least soil nutrients availability. This may be due to leaching effect and nutrients uptake by the vegetation. Soils under bun cultivation had higher bulk density than the soils under forest and shifting cultivations. This difference may be ascribed to repeated tilling and other agricultural practices in bun cultivation. Several studies (Lal et al., 1999; VandenBygaart et al., 2003) have already reported the effect of tillage on bulk density. The CEC was found to be high in all the sites, with the highest amount observed in forest soils. Higher CEC values were observed in soil where higher values of SOC were also observed. The increase in humus content in the soil due to decomposition of litters and other dead plants materials may be responsible for increasing the negative charge on soil colloid which in turn lead to increase in CEC values. Electrical conductivity, available nitrogen, available potassium followed the trends of organic carbon. Regarding available phosphorous, it was observed that almost all soils are deficient in available phosphorous with values ranging from 7.21 to 19.60 kg/ha.

6.6.2 Indicator selection

As per Table 6.2 , the mean values of various soil indicators showed significant differences among various landuse, except for few indicators like available phosphorous, pH, porosity and bulk density. Significant correlation (Table 6.3) was observed for only 4 variables out of 10 chosen soil parameters. This indicates that the selected soil properties respond sensitively to different management. In the present study, PCA followed by varimax rotation was applied to all the selected soil indicators. Result of the analysis grouped the soil data set into four principal components (principal component with Eigen values greater than 1). Together the four-principal component could explain 78% of the total variances in the data set. Communalities column in Table 6.4, indicate how much variance in a particular soil indicator have been accounted in the extracted factors (Wichern and Johnson, 1992). Results indicated that the extracted PCs represent a majority of variables of the soil indicators with values ranging from 53-94 % (Table 6.4). Under PC-1, SOC and available nitrogen were found to be the highest weighted indicator with rotated factor loadings of 0.92 and 0.91 respectively. But since SOC and available nitrogen were found to be highly correlated ($r=0.79$, $P < 0.05$) and in order

Table 6.2: Values of selected soil properties (Different letters at the top, signifies significant differences (P < 0.05) among different LUSM)

Soil Properties	**Landuse**				
	BC (n=19)	**SC (n=18)**	**DF(n=18)**	**PF(n=20)**	**AS(n=18**
	Mean ± SEM	Mean ± SEM	Mean ± SEM	Mean ± SEM	Mean ± SEM
SOC (%)	2.36 ± 0.19^d	3.23 ± 0.25^b	3.46 ± 0.11^a	2.53 ±0.24^c	1.03 ± 0.39e
Avail N (Kg ha-1)	390±9.63^d	490±20.34^b	560± 19.12^a	452± 12.13^c	170±10.17^e
Avail P (Kg ha-1)	19.60 ±1.42^a	17.12 ± 3.32^b	17.82 ±3.12^b	16.01± 3.25^b	7.21± 2.13^c
Avail K (Kg ha-1)	320.80 ±9.67^c	360.12± 8.12^b	420.12± 6.25^a	177.12± 7.25^d	123.12± 20.19^e
pH	5.32±0.46^b	5.64 ± 0.12^a	5.13 ±0.16^c	5.14 ± 0.19^c	4.32 ±0.12^d
BD (g/ cm^3)	1.54 ±0.03^a	1.32 ± 0.04^c	1.23 ±0.03^c	1.21 ± 0.5^c	1.38 ±0.09^b
Porosity	41.88±0.03^c	53.96± 0.04^a	53.58±0.03^a	54.33± 0.9^a	47.92±0.09^b
EC (μS cm^{-1})	21.2±3.6c	26.8± 4.4^b	37±7.6^a	18.9±3.7^d	10.4 ±3.4^e
CEC (cmol (+) kg^{-1})	10.40 ± 0.04^d	15.80 ± 1.2^b	17.60 ± 0.07^a	13.70 ±0.08^c	7.88 ±0.8^e
TN (%)	0.18 ±0.05^d	0.22±0.09^c	0.28±0.04^a	0.25±0.09^b	0.14±0.09^e

Table 6.3: Correlation among soil attributes collected from five landuse (*P =0.05, significant)

	SOC	Avail. N	Avail. P	Avail. K	pH	BD	Porosity	EC	CEC	TN
SOC	1									
Avail. N	0.79*	1								
Avail. P	0.40	0.46	1							
Avail. K	0.06	0.10	-0.07	1						
pH	0.38	0.33	0.40	0.48	1					
BD	-0.58*	0.31	0.07	0.13	0.17	1				
Porosity	0.58*	-0.31	-0.07	-0.13	-0.17	-1*	1			
EC	0.42	-0.37	-0.35	-0.33	0.05	0.43	-0.43	1		
CEC	0.09	0.53	0.48	0.28	-0.29	-0.42	0.42	-0.35	1	
TN	0.30	0.46	0.57	-0.07	-0.41	-0.28	0.28	-0.24	-0.16	1

to avoid redundancy in variable selection, only SOC was selected based on its highest correlation sum. Bulk density was the highest weighted soil indicator (0.86) followed by porosity (-0.86) and CEC (0.83) within PC-2. Since Porosity and Bulk density are highly correlated, only BD is selected based on its highest correlation sum. However, CEC is non-correlated to both BD and porosity, so BD and CEC were retained for minimum data set selection. Likewise, for PC-3, pH and available potassium were retained and since both the variables showed non-significant correlation ($r < 0.40$; $P > 0.05$), they were both retained for minimum data set selection. While for PC-4, only available phosphorous showed highest weighted value (-0.86) and consequently included for indicators selection. Thus, the final indicators included SOC, BD, CEC, pH, available potassium and available phosphorous. The importance of these selected indicators to evaluate the levels of soil degradation has been widely reported in the literature in natural as well as soil management conditions (Shukla et al., 2006; Brejda et al., 2000; Liu et al., 2006). Moreover, these parameters especially SOC, pH, CEC, available phosphorus were often reported in study related to effect of shifting cultivation, as these parameters were reported to be influenced by shifting cultivation practices (Gafur et al., 2003; Okore et al., 2007).

6.6.3 Scoring function and SQI calculation

The chosen indicators were transformed into a score ranging from 0 to 1 using Equations 6.6 and 6.7 as per their favourable and unfavourable function for the soil, respectively. This is the most crucial steps in determining the soil quality index of soil, especially in setting up the critical limits for each soil properties (Masto et al., 2008). Limits are generally chosen from natural ecosystem such as forest land or grassland, which are belief to be less disturbed as compare to other landuse (Liebig et al., 2001). For the present study, values for critical limits were based from literature with condition similar to the study area. Based on this, 'more is better' function is applied to SOC, available potassium, total nitrogen, available nitrogen, available phosphorous, EC and CEC. This is based on the role of these soil properties in defining the soil fertility and nutrients supply and storage in line with what is reported in the study carried out in eastern Himalayan (Singh et al., 2014). For bulk density 'less is better' function was followed while for pH optimum function was considered. For pH the threshold values were considered between 4.5 and 7. Scores for pH was given as per the 'more is better' or 'less is better' function based on whether the pH value of a particular soils was above or below the optimal range. For example, the pH value of forest soil was found to be 5.2, so the score for this particular soil samples is based on 'more is better' function.

Each PC described a specific percentage of variation in the data set. This percentage divided by the total percentage that all the four selected PCs could explain (Table 6.4) gives the weighted factor for particular attributes under a particular PC.
The final resulted normalized PCA SQI equation for study area is:

$$PCA - SQI = 0.35_{SOC} + 0.26_{BD} + 0.26_{CEC} + 0.21_{pH} + 0.21_{AvaiK} + 0.16_{AvaiP} \tag{6.17}$$

6.6.4 SQI for different landuse

To emphasize the impact of landuse on soil quality, SQI ratings for various landuse that were considered in the present study was developed (Figure 6.2) based on weighted factor obtained from PCA result (Equation 6.17). Percentage contributions of the se-

Table 6.4: Result of PCA after varimax rotation for chosen soil properties

Soil Quality Indicator	**Principal Components**				**Communalities**
	PC-1	PC-2	PC-3	PC-4	
SOC	**0.92**	0.04	0.07	0.24	91
Avail N	**0.91**	-0.15	-0.03	-0.29	93
Avail P	0.49	0.10	0.16	-0.76	84
Avail K	0.02	-0.27	0.84	-0.12	83
pH	0.39	0.15	**0.85**	0.06	87
BD	0.53	**0.86**	0.21	-0.26	94
Porosity	0.12	**-0.86**	0.14	0.16	76
EC	0.55	0.37	0.14	0.15	62
CEC	0.06	**0.83**	0.04	0.28	82
TN	0.241	0.12	0.10	0.09	53
% Variance explained	27.41	20.61	17.04	13.06	
Cumulative variance explained (%)	27.41	48.02	65.06	78.12	

lected indicators of defining the SQI of different landuse are demonstrated in radar plot (Figure 6.3). The overall SQI of different landuse were in the following orders: 0.91 (DF) > 0.69 (SC) > 0.63 (PF)> 0.57 (BC) >0.37 (AS). Highest SQI of forest soil can be attributed to its highest SOC content (3.46 %), high CEC value (17.60) and lowest bulk density values (1.23 g/cm^3), where these attributes were the most important soil indicators for the study area. Higher SOC content in forest cover can be related with continuing built up of carbon throughout the years due to minimum anthropogenic activities and maximum carbon contributions from vegetation litters and dead roots and plants. Soils with higher SOC content are often accompanied by lower bulk density values (Wang et al., 2012), the same was observed for this study, where most of the soils with higher SOC content are accompanied with lower bulk density. This explanation holds good for higher SQI values of dense forest. Whereas for shifting cultivation, the presence of high SOC content (3.23 %) make it to be second among the considered LUSM in the present study in term of SQI rating. Increase in carbon content may be probably due to incomplete combustion of the vegetation. Study carried by Nye and

Greenland (1964) also reported to observed an increase in SOC content during initial stage of shifting cultivation and point out that the reason was due to incomplete combustion of vegetation. SQI ratings of bun cultivation and pine forest were significantly higher than the abandoned landuse after shifting cultivation. This was also reflected in higher SOC content, CEC content and lower bulk density values of these landuse compared to abandoned landuse after shifting cultivation. Interestingly, the SQI values of various soils under abandoned land after shifting cultivation showed a lot of variation (as shown in Figure 6.2). The rest period of the soil after period of cultivation may be the reason of this variation, as different soils may re-establish their soil property with time. Thus, the positive and negative impact of shifting cultivation practices depends upon the fallow period. Short fallow periods often failed to restore back the soil properties and leads to declination in soil properties and crop yield (Andriesse and Schelhaas, 1987).

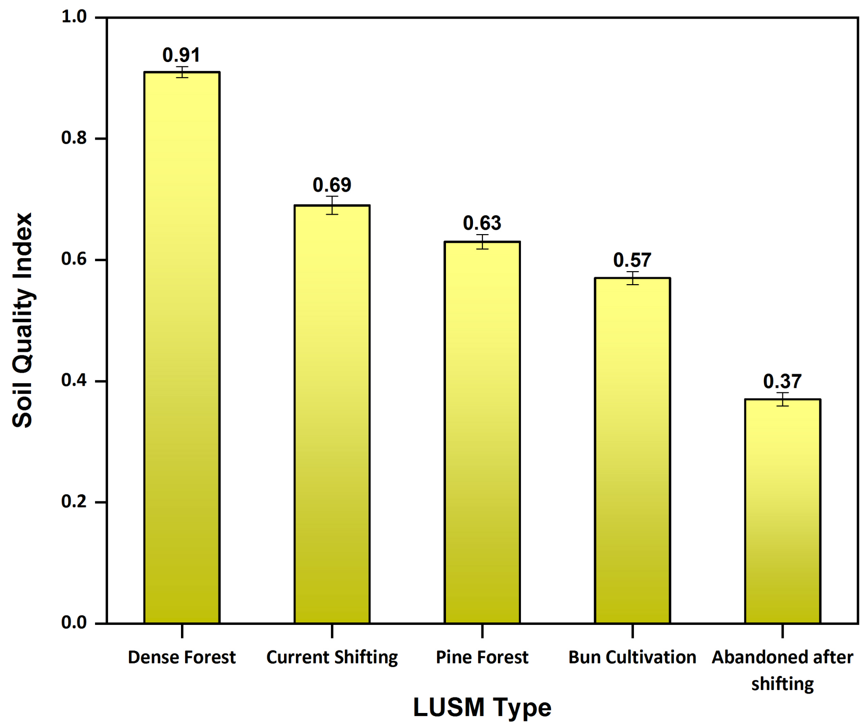


Figure 6.2: Soil quality rating of different LUSM under study (Error bar represents standard deviation ($\times$ 2)).

Overall the percentage contribution of the chosen soil indicators in defining the SQI of various landuse in the present study followed the following orders: SOC (50.6%) > CEC (17.4%) > BD (14.2%) > pH (7.6%) > available potassium (6.8%) > available phosphorus (3.4%). Since classification of soil into different soil quality classes can be helpful for soil management, we therefore categorized the soils of the study area into various classes based on their SQI values (Table 6.5). The soils under dense forest cover were assigned into high quality rating (SQI > 0.80). The soil under abandoned land after shifting cultivation were class into low category (SQI <0.40), where the soils under remaining landuse falls into medium category (0.40<SQI<0.80). The explanations behind their differences in SQI rating have been explained in foregoing discussion. The results stress the need of alternating soil management to improve the soil quality of the present study area especially for those soils which falls under low-medium quality categories.

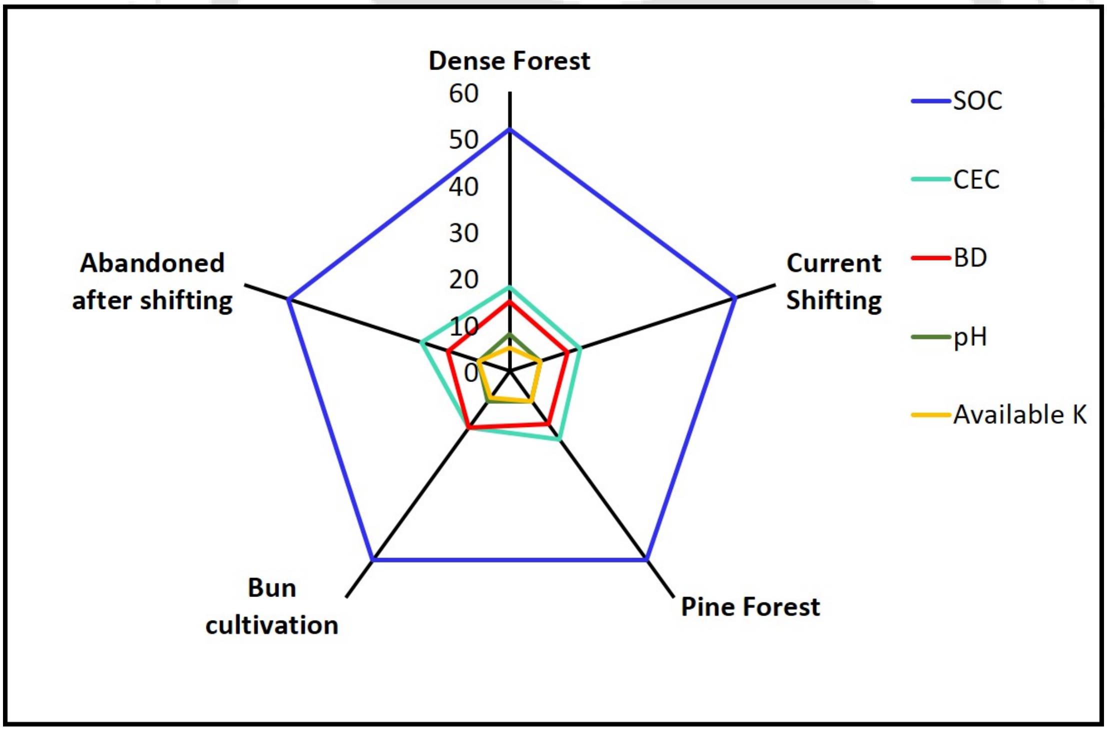


Figure 6.3: Percentage contribution of selector indicators in defining soil quality index of different LUSM under study

Table 6.5: Summary of statistics of soil quality index of different LUSM under study and their classification

LUSM Type	No. of Samples	SQI (mean)	Maximum	Minimum	Soil Quality classification
DF	18	0.91	0.94	0.90	High
CS	18	0.69	0.82	0.62	Medium
PF	20	0.63	0.92	0.49	Medium
BC	19	0.57	0.81	0.42	Medium
AS	18	0.37	0.46	0.29	Low

6.7 Conclusion

Soil quality assessment provides us a way to assess the suitability and sustainability of various landuse and soil management practices prevalent in a region. Present study developed soil quality index to evaluate the effectiveness of five LUSM viz. dense forest, bun agricultural system, Pine forest, shifting cultivation and abandoned land after shifting cultivation. Findings from the study denotes that soil quality index of a study region was highly influenced by landuse and soil management. Soil under dense forest were high in quality rating, whereas soil under Pine forest and bun cultivation practices were class into medium category. Results also highlight the negative impact of shifting cultivation practices on the soil quality of a region. Areas left abandoned after shifting cultivation were found to have the least SQI values. Thus our results stress the need to focuses on reducing land under shifting cultivation practices.

Organic carbon and soil acidity were found to be the major factors controlling the soil quality of the study area under the prevailing LUSM. While SOC improves the quality of the soil, however soil acidification is a great threat to soil quality deterioration. Thus, if soil productivity and quality is to be enhanced in this area, necessary measure needs to be taken to increase the SOC content and ameliorate the acidity of the soils. Practices such as conservation agriculture, application of manure, growing of covers crops which were reported to improve the SOC contents in other regions of the world should be promoted (Pathak et al., 2011; Venkatesh et al., 2013) . Practices such as lime application, application of ammoniacal nitrogen fertilizer which help to reduce the acidity of the soil and improve the nutrients availability (Goulding, 2016) should be popularized. These practices if implemented appropriately could improve the overall productivity and quality of the soils in the study area.

CHAPTER 7

Soil carbon stock and associated resilience analysis under varying climatic conditions across 14 agro-climatic zones of India

7.1 Introduction

On a global scale, temperature and precipitation have been identified as the main factors controlling the distribution of SOC stocks(Parton et al., 1987; Tian et al., 2000; Wang et al., 2014; Gray et al., 2015),yet, no consensus has been made about the magnitude and direction that changes in climatic variables may have on SOC. In recent years, change in climatic variables particularly precipitation and temperature are becoming significant visible and their effects on terrestrial ecosystems are progressively being studied (Campbell et al., 2009; Yigini and Panagos, 2016) However, despite the various studies conducted, the effect of changing climate on SOC is still a subject of continuing debate with some researchers reporting that an increase in temperature may improve the rate of leaf photosynthesis which would result in higher inputs of C into the soil(Olesen and Bindi, 2002; Long et al., 2006), while other studies(Rosenzweig et al., 2001; Schädel et al., 2016) reported that rising temperature will lead to greater emission of carbon from the soil. Similarly, the effect of precipitation is likewise questionable with some reporting precipitation to be beneficial for soil carbon accumulation(Klaminder et al., 2009; He et al., 2012) while others disagree (Fröberg et al., 2008). Hence, with global warming and its likely effect on climatic variables, knowledge of how SOC will respond to these changes is important for global environmental management and food security.

The dependence of SOC on climatic variables can be modeled using a classical approach such as multivariate probability distribution(Nalley et al., 2012). However, the study of the dynamics of the variables related to the natural phenomenon often follows complex spatial and temporal distributions. Essentially, soil and climatic variables present one of the most complicated variability and interdependence which are difficult to understand. Hence, a Gaussian method which works well only with a normal distribution may lead to wrong interpretation of dependencies of climatic variables on SOC. Copula a multivariate probability distribution have gained a lot of attention in various fields these days, as they are able to measure a broader form of dependency and are capable of modeling the independent structure among random variables irrespective of their marginal distribution(Nelsen, 2006; Madadgar and Moradkhani, 2013) . Copula has already been applied to study complex hydrological parameters and climatic variables relationship, vegetation, and climatic variables dynamics. In this study, a similar concept is applied to study the climatic and soil properties (in this case, SOC) relationship from a joint probability perspective. As per the author's knowledge, no study has assessed the impact of global warming induces in the form of changes in climatic variables on SOC content through a probabilistic approach. Most of the studies that have already explored the relationship between SOC and climatic variables used correlation coefficient, structural equation models, linear regression models, or other relevant measures(Jobbágy and Jackson, 2000; Herold et al., 2014; Di et al., 2018). Thus the probabilistic approach may offer important additional insights into SOC response to climate variability.

Given that impacts of climate extremes can be considered as disturbances, it is important to know whether the soils have enough carbon to be resilient against these likely changes. The amount of carbon content presents in the soil play an important role in preserving its properties which are related to its resilience(Lal, 2015). Increase in SOC level content improves the soil porosity(Franzluebbers, 2002) with the result that more water will be stored in the soil and ultimately improve its drought resilience as plants would be able to thrive even during a dry spell. Also, more is the carbon content more will be the productivity of the soil, which lead to abundant vegetation growth(Eschen et al., 2006). Soils with less carbon content will have less vegetation cover and are ultimately exposed to negative impacts of various physical degradation process (e.g. impact of a raindrop) leading to erosion and other effects (Olson et al., 2016). Therefore, soils with greater SOC content will provide greater resistance and resilience to various physical degradation activities. Thus, carbon is the key building resilience in the soil and can be used as one of the proxies to define the soil resilience capacity of a soil.

The aim of this objective is to understand the soil carbon dynamics under varying climatic conditions across the different agro-climatic zone of India. To do so, the study focused on modeling the joint probability of SOC and climatic variables. This joint probability will enable us to find the probability occurrence of SOC and its sensitivity to different climate scenario. Then the study analyzed whether the soil of the various agro-climatic zone has enough carbon to be resilient against these changes. For this, a resilience index was defined in term of soil carbon.

7.2 Materials and Methods

All the previous objectives were carried out at the state level (Northeast India) and regional level. However, for this objective, an attempt was made to carry out on all India basis. With the evaluation of SOC stock and its future projections regularly includes scales as big as global or continental, therefore India with a total geographical area (TGA) of 328.7 Mha, made up of heterogeneous and complex climate, vegetation and soil type, provides an ideal background for studying SOC on large scale. The planning commission of India has made an attempt to divide the country into fifteen agro-climatic zones based on physiography, geological formation, climate, available irrigation resources, and soils types. In this study, the shape files of 14 agro-climatic regions (excluding islands) were created, and analysis was then carried out in each of these regions. The name of 14 agro-climatic zones and their location are shown in Figure 7.1.

The present study used a soil carbon density map extracted from the National Re-

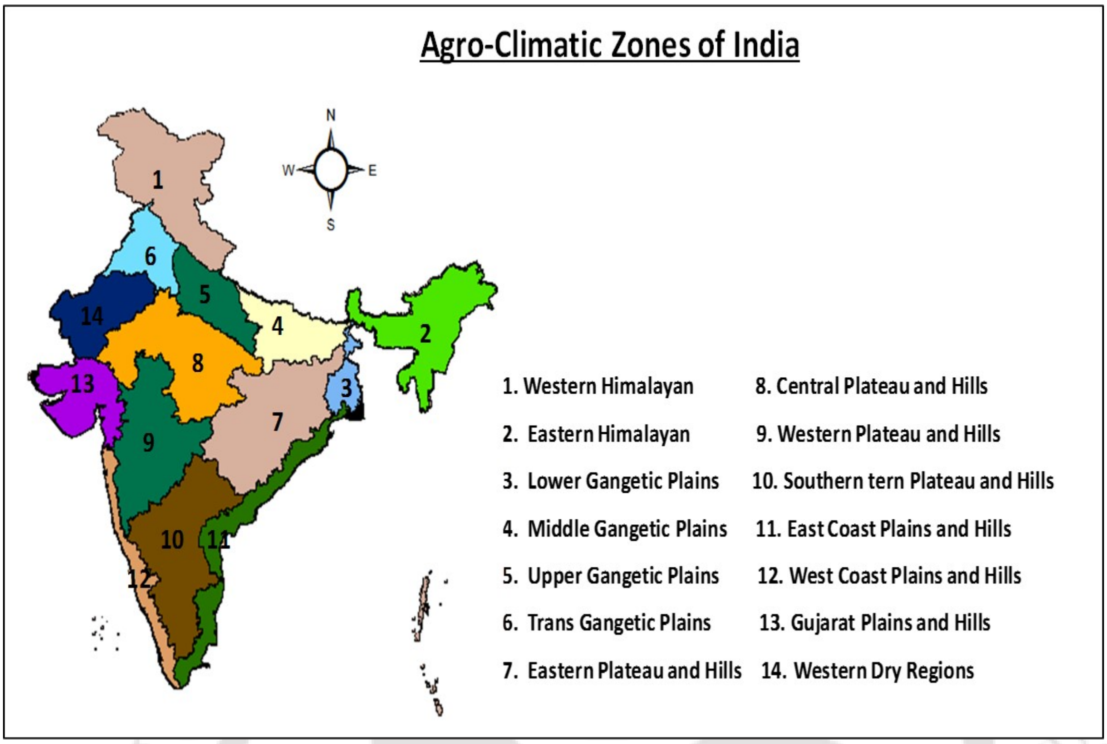


Figure 7.1: Agro-climatic Zone of India

mote Sensing Centre (www.nrsc.gov.in). Soil carbon map is available from this website for entire India at 5 km × 5 km grid resolution. This soil carbon map was produced under national soil carbon pools of India- ISRO-Geosphere Biosphere project carried out during a period of 1985-2005. Climate data, the average mean annual precipitation with a 0.25°×0.25°resolution and the average mean annual temperature with a 1°× 1°resolution for a period of 1985-2005 were obtained from India Meteorological Department (IMD), Pune. The period for climatic data was chosen to match with the soil organic carbon data. All the data used in this study were resampled into a common resolution of 0.25°×0.25°scale before analysis.

7.2.1 Probabilistic analysis of the dependence of SOC on climatic variables

Copula serves as an elegant method to model the joint dependence of SOC and climatic variable. Therefore, in the present objective, we model the joint probability of soil carbon associated with one of the climate variables using Copula. As per Sklar's theorem (Sklar 1959), the joint probability distribution of SOC (denoted by Y_1) and temperature (or precipitation) (denoted by Y_2)F(y_1, y_2) can be defined using a Copula as follows:

$$F(y_1, y_2) = C(F_{Y_1}(y_1), F_{Y_2}(y_2)) = C(u_1, u_2) \tag{7.1}$$

Here $F_{Y_1}(y_1)$and$F_{Y_2}(y_2)$ denotes the marginal probability distribution of SOC and temperature (or precipitation).u_1, u_2 represents the cumulative probability distribution (CDF) of y_1 and y_2 respectively, whereas C is a Copula.

Before finding the best Copula, we first evaluate the best marginal distribution of each of the variables. We determine the best marginal distribution of a variable by comparing the six commonly-used probability distributions including normal, Gumbel, gamma, exponential, Weibull and lognormal. The best marginal distribution of each of the variables was decided based on the Kolmogorov-Smirnov test (Wilcox, 2005). Similarly, we choose three copula function.The copula function chosen in this study are:

Frank Copula (Archimedean family)

$$C(u_1, u_2; \theta) = -\frac{1}{\theta} ln[1 + \frac{(e^{-\theta_{u1}} - 1)(e^{-\theta_{u2}} - 1)}{e^{-\theta} - 1}] \tag{7.2}$$

Where θ is range from$(-\infty, \infty)$.

Plackett Copula

$$C(u_1, u_2; \theta) = \frac{S\sqrt{S^2 - 4u_1, u_2\theta(\theta - 1)}}{2(\theta - 1)} \tag{7.3}$$

Where $S = 1 + (\theta - 1)(u_1 + u_2)$ and range of θ is from$(0, \infty)$.

Gaussian Copula (Elliptical family)

$$C(u_1, u_2; \theta) = \emptyset_\theta[\emptyset^{-1}(u_1), \emptyset^{-1}(u_2)] \tag{7.4}$$

where range of θ is from$(-1, 1)$.

Note: $\emptyset^{-1}$ denotes inverse standard normal distribution function and $\emptyset_\theta$ represents the bivariate standard normal distribution function with Pearson linear correlation coefficient θ.

Although there are many copula families, but often most of the copulas are suitable only for either positive or negative variables(Zhang and Singh, 2007). However, the above three chosen copulas from different copula families are suitable for both positive as well as for negatively correlated variables, hence they are chosen for the study. The best-fit copula among Plackett, Frank, and Gaussian that best describes the dependence structure of variables and connect their marginal distribution was selected based on Akaike information criterion (AIC) (Akaike, 1974) and Bayesian information criterion (BIC) (Vrieze, 2012)

The AIC and BIC values are calculated as:

$$AIC = 2(k) - 2\ln(L) \tag{7.5}$$

$$BIC = 2ln(L) - 2ln(N) \tag{7.6}$$

Here, k is the number of parameters, L is the maximized value of the likelihood function and N is the sample size.

With joint probability distribution of SOC and temperature (or precipitation) defined in equation 7.1, a conditional probability distribution of SOC under a given temperature or precipitation can be now developed. For an application, one might be interested to evaluate the particular conditional probability of $Y_1 \leq y_1$ given $Y_2 \leq y_2$, which can be defined using a Copula as follows:

$$F_{Y_1 \leqslant y_1 | Y_2 \leqslant y_2}(y_1, y_2) = \frac{C(F_{Y1}(y_1), F_{Y2}(y_2))}{F_{Y2}(y_2)} = \frac{C(u_1, u_2)}{u_2} \tag{7.7}$$

Equation 7.7 is used to calculate the condition occurrence of SOC under a given condition of temperature or precipitation.

In the present study, we simply choose the probability of occurrence of SOC in a particular agro-climatic zone to be high if the SOC value is more than the 60th percentile of SOC across each agro-climatic zone. We evaluate the occurrence of SOC on two temperatures (or precipitation) scenarios. The first scenario is the non-exceedance of temperatures (or precipitation) of 20th percentile which was calculated from data of the years 1985-2005, denoted as $U_T \leq 20\%$ (or $U_P \leq 20\%$). The second scenario is the non-exceedance of 60th percentile calculated from the same data set, denoted as $U_T \leq 60\%$ (or $U_P \leq 60\%$). These percentiles represent the abundance (60%) and scarcity (20%) of the climatic variables and are chosen to illustrate how extreme changes in climatic variables may have an impact on SOC content. It should be noted, that one may decide their own threshold value (percentile) of SOC, precipitation, temperature, once the joint probability distribution function has been constructed. This analysis allows us to determine the regions where SOC is sensitive to changes in precipitation and temperature.

7.2.2 Soil resilience capacity

We define an index R_s to quantify the resilience capacity of each agro-climatic zone of India using the amount of SOC as an indicator, where Rs is the ratio of the mean value of SOC content in an agro-climatic zone to the overall mean of SOC.This index was defined based on the conclusion of Greenland et al. (1975) who reported that soils that have less than 2 % of SOC are prone to destruction. Considering the amount of soil organic carbon for the topsoil (up to 20cm) with carbon value of 2 % assuming the bulk density of 1.6 g/cm^3 (critical value for plant growth) is approximately 6.4 kg/m^2 (without taking into account the amount of gravel content). The mean SOC of the country as per the data during the study period was found to be 6.530 kg/m^2 (close to 6.4). Therefore, for the period of study duration, the agro-climatic zone that maintains its mean SOC equal or greater to the overall mean SOC of the country is considered as resilience.

Different classes were devised with respect to the value of Rs. If Rs is greater than or equal to 1, the soil of that particular agro-climatic zone is term resilient to disturbances, If Rs lies between 0.9 and 1, the soil of the agro-climatic zone is termed as slightly non-resilient. If Rs is between 0.8 and 0.9, the soil of the agro-climatic zone is termed as moderately non-resilient and if Rs is less than 0.8, the soil of the agro-climatic zone is termed as severely non-resilient to disturbance.

$$R_s = \frac{\text{Mean SOC of each agro climatic Zone}}{\text{Overall mean}} \tag{7.8}$$

7.3 Results

7.3.1 Copula-based approach

A number of probability distribution viz. normal, Gumbel, gamma, exponential, Weibull and lognormal were examine using the Kolmogorov–Smirnov test to find out the best fit marginal for SOC, temperature, and precipitation of each agro-climatic region. In Table 7.1, for illustration, we have only shown the Kolmogorov–Smirnov statistics value of SOC, precipitation, and temperature of four agro-climatic regions of India, however, for analysis, the test was carried for all the regions. The result of KS test in Table 7.1 indicated that in Central Plateau and Hills, normal distribution represents the best marginal distribution for all the four variables, however in regions like Eastern Himalayan, Middle Gangetic plain, East Coast Plains and Hills, the best marginal distribution differs from one variable to another. Hence copula method which is capable of modeling the joint distribution of variables irrespective of their marginal distribution is used to model the joint distribution of SOC and climate variables.

A copula function is needed to model the joint distribution of SOC with each climate variables. The best-fit copula family out of Gaussian, Frank, Gumbel was chosen based on Akaike information criterion (AIC) and Bayesian information criterion (BIC). The preferred copula family is the one with the minimum AIC and BIC values. Best Copula function between SOC and each climate variables for all agro-climatic region is shown in Table 7.2. With the best copula function and its parameter, we then model the joint probability of SOC (denoted by Y_1) and temperature (or precipitation) as shown in equation 7.1. Once the joint probability distribution of SOC with climates variables within each Agro-climatic regions has been derived, we then used a conditional probability (equation 7.7) to examine the sensitivity of occurrence of SOC to various climatic conditions.

The conditional occurrence of high SOC content ($U_{SOC} \geq 60\%$) under the two precipitation scenarios($U_P \leq 20\%$) and $U_P \leq 60\%$) is shown in Figure 7.2. The conditional probability value in each agro-climate zone can be interpreted as the likelihood of occurrence of the higher value of SOC content under given precipitation or temperature level, with lower value indicated a lower likelihood of occurrence. Figure 7.2 indicated that an increase in precipitation level will have a greater likelihood of occurrence of high SOC content of varying magnitude in regions like Upper Gangetic Plain, Transgenic Gangetic plain, Gujarat Plain and Hill, Central Plateau and Hill, Western Plateau and Hill, Southern Plateau and Hill, and Western dry region. For instance, in Upper Gangetic Plain the conditional probability of occurrence of SOC increased by 0.11 when we increased the precipitation level from $U_P \leq 20\%$ to $U_P \leq 60\%$, whereas in Central Plateau and Hill the conditional probability value increased by 0.10. Since the conditional probability of occurrence of SOC content greatly varies under different precipitation scenario, this denotes the dependencies of SOC on precipitation in these regions and the difference in the conditional probability of two scenarios represents the magnitude of their dependencies. However, in regions like Western Himalaya, Lower Gangetic Plain, Eastern Plateau and Hills, East Coast Plain and Hill, West Coast plain and Hills, Eastern Himalaya and Middle Gangetic plain, SOC content exhibit non-significance differences under different precipitation level (Figures 7.1 and 7.2). This result enabled us to identify the agro-climatic zone where SOC content is sensitive to precipitation. The conditional occurrence of high SOC content under the two temperature scenarios (Figure 7.2) indicated that an increase in temperature will have a negative influence on probability of occurrence of SOC content of varying magnitude in the regions like Upper Gangetic Plain, Transgenic Gangetic plain, Gujarat Plain and Hill, Central Plateau and Hill, Western Plateau and Hill, Southern Plateau and Hill, Western Dry region and in East Coast Plain and Hill. However, an increase in temperature in areas like Western Himalayan, Eastern Himalayan, Lower Gangetic Plain, Middle Gangetic Plain, Eastern Plateau and Hills, and West Coast Plains and Hills shows to have a relatively small positive influence on the occurrence of SOC. This result enabled us to identify the agro-climatic zone where SOC content is sensitive to temperature.

It should be noted here, that one can evaluate the likelihood of occurrence of SOC and generate a probability distribution map of SOC for any self-defined threshold of SOC and precipitation or temperature, once the joint probability distribution function has been constructed.

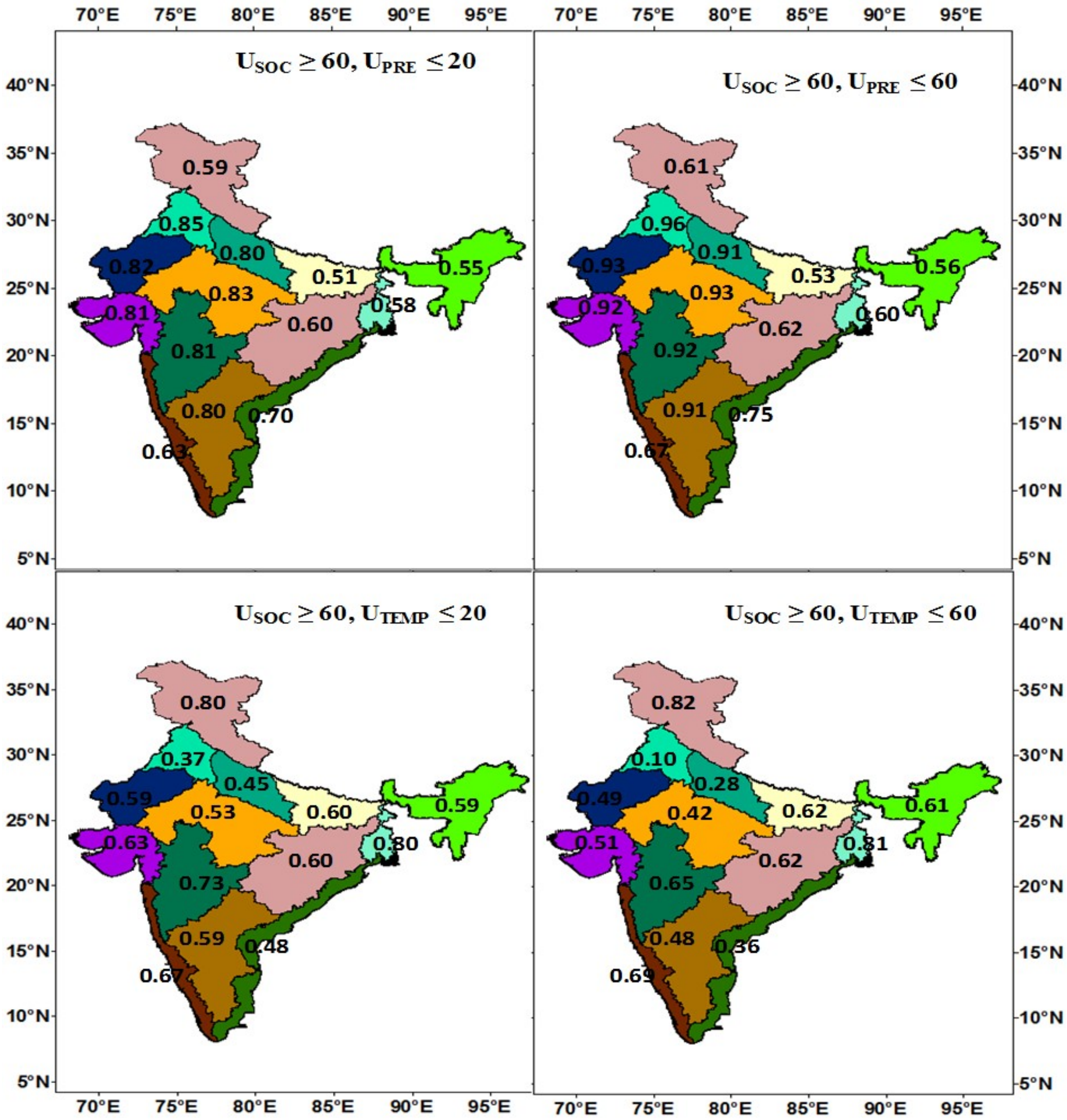


Figure 7.2: Likelihood occurrence of high SOC content of high SOC content for a particular threshold ($U_{SOC} \leqslant 60\%$) under two climates scenarios (20 and 60 percentiles)

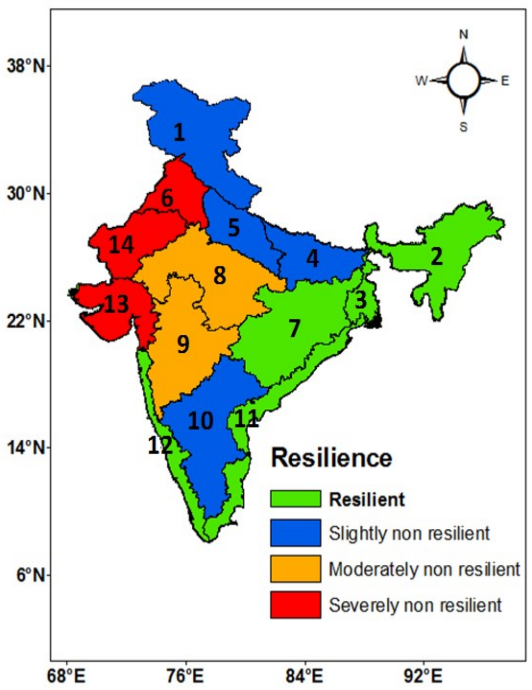
Table 7.1: Kolmogorov–Smirnov statistics of different marginal distributions for Soil organic carbon (SOC), temperature(TEMP), precipitation(PRE) and soil moisture content (SOM) of 4 agro climatic region of India.

Region		Normal	Gumbel	Gamma	Exponential	Weibull	Log normal
East Coast Plains and Hills	SOC	**0.165**	0.181	0.810	0.259	0.585	0.535
	TEMP	0.143	**0.109**	0.582	0.351	0.487	0.502
	PRE	**0.044**	0.106	0.514	0.253	0.433	0.495
	SOM	**0.096**	**0.096**	0.472	0.192	0.396	0.499
Middle Gangetic Plains	SOC	0.364	**0.352**	0.637	0.422	0.539	0.511
	TEMP	0.065	**0.063**	0.587	0.335	0.491	0.51
	PRE	**0.132**	0.241	0.587	0.296	0.497	0.501
	SOM	**0.064**	0.115	0.511	0.205	0.432	0.494
Eastern Himalayan	SOC	**0.142**	0.187	0.688	0.468	0.568	0.514
	TEMP	0.142	**0.114**	0.541	0.393	0.463	0.499
	PRE	**0.162**	0.298	0.418	0.201	0.353	0.483
	SOM	0.067	**0.066**	0.516	0.349	0.439	0.499
Central plateau and Hills	SOC	**0.184**	0.275	0.586	0.294	0.506	0.51
	TEMP	**0.092**	0.13	0.517	0.417	0.449	0.494
	PRE	**0.074**	0.075	0.384	0.202	0.315	0.48
	SOM	**0.092**	0.108	0.395	0.225	0.331	0.474

The best-fitted marginal distributions are display in bold.

7.3.2 Soil ecosystem resilience of different agro-climatic zones of India

Figure 7.3 shows the resilience capacity of each agro-climatic zone of India. A higher value of Rs indicates a higher resilience capacity of the region. Results indicated that out of 14 agro-climatic zones of India (the island is excluded in this study), only 5 agro-climatic zones were found to be resilient during the study duration (Figure 7.3). These 5 agro-climatic zones cover approximately 1/3 of the total geographic area of India, the remaining portion of agro-climatic zone of India were therefore non-resilient to different degrees. West coast Plains and Hills had the highest Rs (1.840) followed by Eastern Himalayan (R_s = 1.631), Eastern Plateau and Hill (R_s = 1.297), Lower Gangetic Plains (R_s = 1.095) and East Coast Plains and Hills (R_s = 1.083). Western dry agro-climatic zone of India was found to have the least resilient (R_s = 0.383))



Agro-climatic-Zone	R_s	State of Resilient**
1	0.980	SNR
2	1.631	R
3	1.095	R
4	0.921	SNR
5	0.947	SNR
6	0.769	SeNR
7	1.297	R
8	0.859	MNR
9	0.836	MNR
10	0.904	SNR
11	1.083	R
12	1.840	R
13	0.582	SeNR
14	0.383	SeNR

Figure 7.3: Soil resilience of different agro-climatic zones of India (For $R_s \geqslant 1, 0.9 - 1, 0.8 - 0.9, < 0.8$, the soil is termed resilient to disturbances (R), slightly non-resilient (SNR), moderately non-resilient (MNR), severely non-resilient to disturbance (SeNR), respectively)

7.4 Discussion

7.4.1 Impact of climatic variables on SOC of different regions

The present study developed a copula probabilistic model to evaluate the joint dependence of SOC and climatic variables (temperature or precipitation). This enables us to assess the probability of occurrence of SOC content conditioned to a different temperature or precipitation levels across the different agro-climatic zone of India. To the best of author's knowledge, this study is the first to assess the impact of global warming induces in the form of changes in precipitation and temperature on SOC con-

Table 7.2: Best Copula function between SOC and precipitation or temperature for all Agro-climatic regions

	Agro-climatic region													
	Cen tral pla teau and hill	East coast plain and hill	Eas- tern plateau and hill	Eas- tern Hima layan	Guja rat plain and hill	Lower Gang- etic plain	Middle Gang etic plain	South- ern plateau and hill	Trans- Gang- etic plain	Upper Gang- etic plain	West coast plain and hill	West- ern Dry	Wes- tern plain and hill	Western Hima layan
SOC_ Precipi tation	Plac kett	Plac kett	Plac kett	Plac kett	Plac kett	Plac kett	Plac kett	Plac kett	Plac kett	Gaus sian	Plac kett	Plac kett	Plac kett	Plac kett
SOC_ Tempe rature	Plac kett	Frank	Frank	Plac kett	Gaus sian	Gaus sian	Gaus sian	Frank	Frank	Plac kett	Plac kett	Frank	Frank	Gaus sian

tent through a probabilistic approach. The SOC content of agro-climatic zone most sensitive to temperature or precipitations changes were identified. On the global scale,

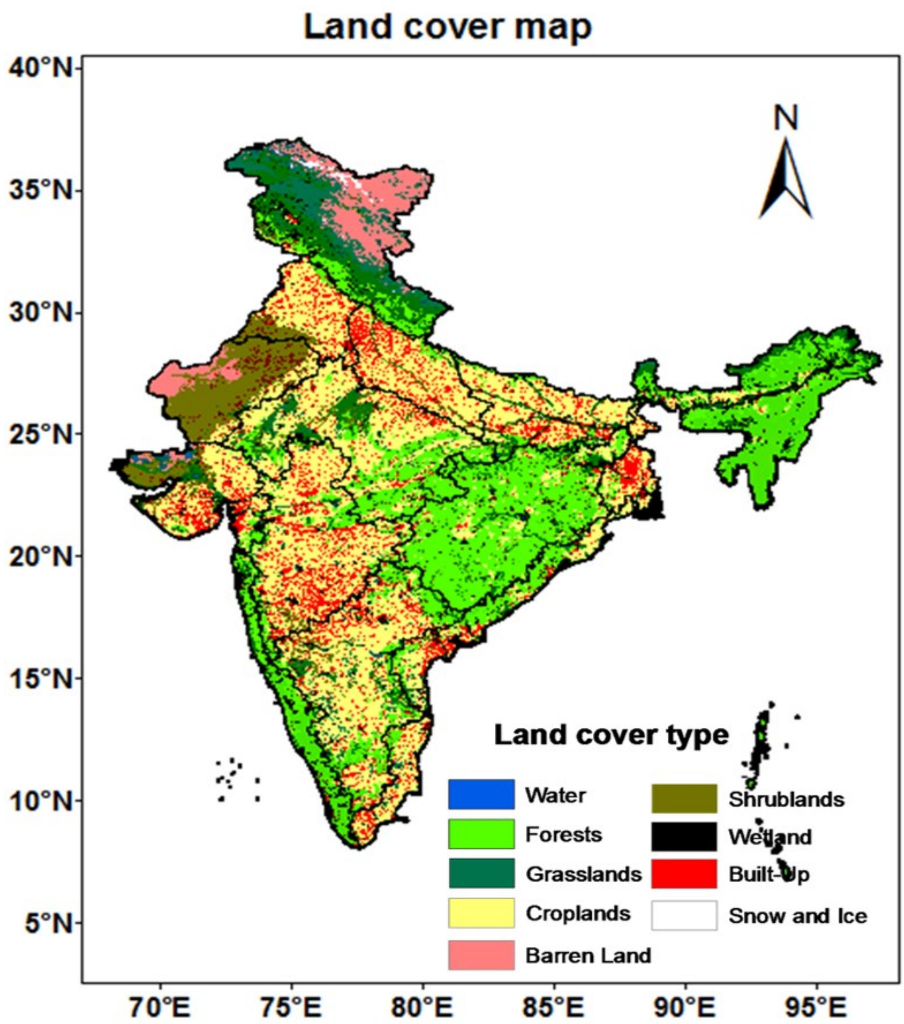


Figure 7.4: Land cover map (Obtained from MODIS)

SOC has been reported to increase with increases in precipitation and decrease with increase in temperature(Post et al., 1982). However, the results of this study indicated that the spatial pattern of the effect of precipitation and temperature on SOC content varies markedly across the different climatic zone. Compared to the other regions, it is observed that the SOC stock of the agro-climatic zones located in semi-arid and arid regions, viz. transgenic Gangetic plain, Gujarat Plain and Hill, Western dry region, Central plateau and Hill, Southern plateau and hill, Upper Gangetic plain and Western Plateau and Hills is relatively more sensitive to changes in precipitation and temperature (Figures 7.1 and 7.2). In these regions, it is observed that the likelihood of occurrence of SOC increases with the increased level of precipitation, indicating the greater dependencies of SOC on precipitation level. As with soil carbon storage, the majority of the carbon inputs comes from plant productivity (Kuzyakov and Domanski, 2000), therefore, a possible explanation for the increase of likelihood of high SOC content with higher precipitation level, may be in humid and semi-arid environment which generally associated with lower amount of annual precipitation, increase in precipitation level will improves the plant water availability and the length of growing season(Doorenbos and Kassam, 1979), leading to greater plants productivity which could lead to a positive effect on SOC(Bell et al., 2010).The likelihood of occurrence of SOC content however was observed to decreases with increase in temperature level in these regions. The possible explanation for this may be, these regions with extreme temperature, a further increase in temperature in such kind of environment will lead to higher evaporation losses which will aggravate the plant water availability crisis and thus affect the SOC content (Bodner et al., 2015).

The SOC stock of agro-climatic zones such as Eastern Himalayan, West Coast Plains, and Hills, Eastern Plateau and Hills, Lower Gangetic Plain, Middle Gangetic Plain, were observed to be relatively less sensitive to changes in precipitation and temperature, even though a small positive influence on SOC was observed with an increase in temperature (Figures 7.1 and 7.2). A small positive influence on SOC content may be due to relatively influence of temperature on net primary productivity in these regions. Past studies such as Bentz et al. (2010) indicated that a slight increase in temperature will have a positive effect on forest net primary productivity, which are the sources of soil carbon. These agro-climatic zones especially Eastern Himalayan, West Coast Plains, and Hills, Eastern Plateau and Hills have the highest density of forest cover (Figure 7.4), hence changes in temperature may influence the net primary productivity of these forest cover which may affect their SOC content.

With temperature is predicted to increase everywhere under climate change, these findings stress the need that future study should further investigate the effect of increase in temperature on net primary products and SOC content of various forests types and vegetation cover.

7.4.2 Resilience capacity of agro-climatic zones of India

SOC is an important soil property which can be used as an indicator to determine the loss of soil health or quality. We used SOC as an indicator to determine the resilience capacity of each agro-climatic region. Resilience capacity varies from region to region because climatic and other factors vary spatially across the study area. These factors affect the SOC amount and ultimately affect soil's resilient capacity. Our study shows that only 5 agro-climatic zones (out of 14) will be able to retain or restore their quality against disturbance as per the amount of SOC content present during the study duration. West Coast Plains and Hills, as well as Eastern Himalayan, have the highest resilient capacity. The presence of thick forest vegetation (Figure 7.4) can be attributed to the highest SOC stock and ultimately boost up the resilient capacity of these areas (Bhattacharyya et al., 2000). Agro-climatic regions such as Central Plateau and Hill, Gujarat Plain and Hill, Trans Gangetic Plains, Western Dry, Western Plateau, and Hills were found to be moderately and severely non-resilient. Farmers in these regions do not use sufficient amount of nutrients because of the uncertainty in the amount of rainfall, which may affect their crop productivity and economic status, and ultimately lead to low carbon input into the soil (Sharma et al., 2009). Thus, unless sufficient adaptation measures are taken, changing climate will be a threat to the soils of these regions, and these areas may remain as a bane to Indian agriculture. To combat such situation and to prevent the degradation of the soil of those regions, one needs to strategically strengthen the quality and resilient capacity of Indian soils. Improvement and restoration of SOC balance are needed by appropriate management related to the local specific situation.

7.4.3 Outlook: On improving the prediction of SOC due to changes in climatic variables

Effect of changes in climatic variables on SOC differ between ecosystem types and may change even diurnally and seasonally. In the current study, soil carbon data used is an annual average carbon pool obtained from a project carried out during a period of 1985-2005. This data was used with the hypothesis that changes in SOC occur gradually with time. However, in reality, the carbon storage may be altered by seasonal inputs coming from plants residue. Thus, timing is a very crucial factor and future study should concentrate on dependence between SOC and climatic variable during each month of a growing season.

Also, the current study uses bivariate conditional model for analysis, however, in reality, two extreme events may also occur together (e.g. high temperature and high precipitation), therefore future study should also an emphasis on the trivariate or multivariate conditional model. Also one should note that human disturbance (e.g. deforestation etc.) may alter the direct influence of climate variables on soil carbon.
However, even with these limitations, the proposed methodology of probabilistic assessment of SOC and climatic variables provides information for soil carbon management and climate-related policy as compared to deterministic methods. Such an approach can be applied to other regions worldwide to monitor and predict SOC under changing the climate.

7.5 Conclusion

Results of this study facilitate the understanding of how the SOC content of various agro-climatic zones of India will likely respond to changing in temperature and precipitation conditions. The soil carbon content of various agro-climatic zones was found to respond differently under different scenarios. Results are also compelling as they highlight that many agro-climatic zones of India are non-resilient and sensitive to changes in climatic variables. In fact, only$\frac{1}{3}$ of agro-climatic zones of India were found to be resilient during the study duration. Importantly, results indicate that unlike other climatic zones, soils from more arid and warmer sites (Agro-climatic zone) were found to associated with lower soil carbon content and are more sensitive to changes in precipitation and temperature level. With precipitation is predicted to decrease in most of the semi-arid and arid regions(Huang et al. 2016) and the temperature is predicted to increase everywhere under climate change, this may pose a threat to the quality and resilient of the soils of these areas unless sufficient adaptation measures are taken. Our results stress the need of exploring and identifying sites specific management practices which are regions specific, so as to improve the soil health and resilient capacity of the country for food security and environmental management.

CHAPTER 8

Soil properties enhancement from vermicompost management enriched with biofertilizers

8.1 Introduction

The problem of soil carbon loss, climate change and food security which may characterize our future, can be tackled through improvement of various soil physiochemical properties particularly soil organic carbon (Roldán et al., 2003; Bhattacharyya and Mukherjee, 2009).Among the various initiatives debated to mitigate climate change, one of the popular option is sequestration of carbon in agricultural soil.

Biological processes such as vermicomposting has been widely recognised as one of the excellent soil amendment and bio control agent (Zaman, 2013). Vermicomposting is an organic waste decomposition method with addition of earthworm to help in waste stabilization process (Lim et al., 2015). Application of vermicompost showed better outcomes in contrast to chemical fertilizers as far as crop yield and soil physical and chemical properties are concerned (Lazcano and Domínguez, 2011). Biofertilizer is another substance that is expected to reduce the use of synthetic minerals and fertilizers (Wu et al., 2005). Biofertilizer contains living organisms derived from roots and cultivated soils which when applied help to restore the soil's nutrients and build soil organic carbon (Vessey, 2003).Application of biofertilizers, vermicompost and another form of composts are known to improve the soil properties such as soil organic matter by improving the soil structure (Baiano and Morra, 2017). In fact, the effect of organic amendment input on the storage and long term stabilization of soil carbon is defined by its relationship with soil aggregates(Kleber et al., 2011; Schmidt et al., 2011) .Soil aggregate distribution controls soil pores size and soil connectivity which in turn control microbial activity and soil carbon decomposition and stabilization (Mpeketula and Snapp, 2018) . A lot of literature has already proved that application of organic amendment on soil showed variables rate of improvement on soil aggregation and soil carbon storage (Du et al., 2014; Tiemann and Grandy, 2015; Mpeketula and Snapp, 2018). However, studies on microbial enrichment of vermicompost with biofertilizers at different dosages in relation to the improvement of soil aggregate distribution, soil physical and chemical properties and crop yield are still very limited. (Mahanta et al., 2012; Gopinathan and Prakash, 2014).

Okra popularly known as Ladies finger is a popular vegetable crop which is predominantly grown in tropical and subtropical regions of India. This crop is known to be a good source for carbohydrates, minerals and also provides various other health benefits (Gemede et al., 2015). Okra crop is grown twice in a year, generally during spring-summer and during rainy season. This study, therefore, chose okra to examine the changes in soil aggregate distribution, soil physical and chemical properties and crop parameter (in this case crop height) in response to the different concentration of vermicompost enriched with bio-fertilizers. The choice of fertilizers was on the basis that it is sustainable and cost effective.

Therefore in this objective, an experiment was conducted to investigate the effect of microbial enrichment on vermicompost on mean weight diameter of aggregate, distribution of aggregate, soil physical and chemical properties and on crop parameter.

8.2 Study area

The field experiment study was carried out in Amingaon (26.1929°N, 91.6951°E) situated on the northern bank of Brahmaputra River in Assam. Assam receives an average annual rainfall of 2000 mm per year. Temperature in the state ranges from 35-38°C during summer to 6-8°C during winter (Jain et al., 2013). Okra crop provide good yield in warm humid condition with its temperature requirements ranging from 23-36°C and it can successfully grow even in region of heavy rainfall (Adilakshmi et al.,

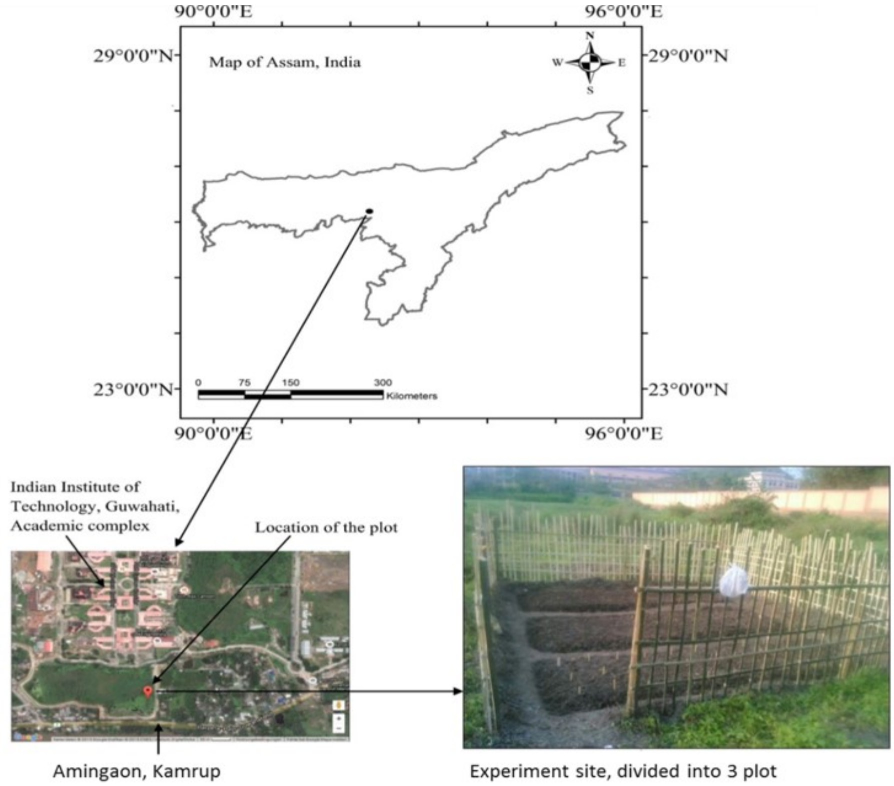


Figure 8.1: Location of the experimental plot.

2010). Hence Okra will be highly suitable for the study area.

8.2.1 Experimental design

The site was divided into three plots, each with an approximate dimension of about 1.5 m x 3 m which is bordered by bamboo fencing as shown in Figure 8.1. Each of these plots was subjected to different fertilizers treatment. Field 1 is a control unfertilized plot, Field 2 and Field 3 is applied with Vermicompost enriched with Bio-fertilizer but with different doses. The treatments were as follows:

$$\text{Field 1- Control unfertilized plot} \tag{8.1}$$

$$\text{Field 2- Vermicompost (1.5 t ha-1)} + \text{Azotobacter (1.5 t ha-1)} \tag{8.2}$$

$$\text{Field 3- Vermicompost (3.5 t ha-1)} + \text{Azotobacter (1.5 t ha-1)} \tag{8.3}$$

Azotobacter is a biofertilizer which is made up of free-living nitrogen-fixing bacteria that can promote plants growth and soil properties(Lima et al., 2010). Vermicompost used in the study was made mostly from farmyard manure and was bought from the local company. The vermicompost properties are pH,7.8; Organic carbon, 294 g kg^{-1}; 152 g kg^{-1} total nitrogen. Tillage was done up to 30 cm depth with the help of spades. The fertilizers were properly incorporated into the plow soils by tillage. The treatments combination was repeated four times. The crop was first grown in the early season (15 April 2016) and the second cropping season was carried in the late season (20 August 2016). The third and fourth season was carried on the month of April and August of the year 2017 respectively. The plant's residue at the end of each growing seasons was chopped and buried into the field.

8.2.2 Soil sampling and analysis

Soil samples from all the three plots were collected prior to the commencement of the experiment and at the end of each growing seasons (up to a depth of 30 cm) with the help of soil core. During sampling, three soil samples were taken randomly from each plot and merged together to form a composite sample. The collected soil samples were kept on a zip-lock plastic bag. The soil sample was then air dried and then divided into two parts. One part was grounded and made to pass through 2 mm sieve. The soil that is less than 2 mm are soil for determination of soil physical and chemical properties, and the other ungrounded portion was used for aggregate size distribution analysis. The concentration of SOC, pH, EC, were determined using standard procedures described in the previous chapters.

8.2.3 Aggregate size distribution

The bulk soil collected from each plot was divided into three classes: large macro aggregate > 2 mm, small macro-aggregate (0.25$-$2 mm) and micro-aggregate (< 0.25 mm) as defined by Wortmann and Shapiro (2008). The bulk soil was made to pass through a 4.75 mm. The crop residues, roots, and materials retained on the 4.75 mm sieve were discarded. The soil which passes through 4.75 mm from each plot was then evaluated for water stable aggregate using wet sieving method. The steps conducted are as follow: First, a 2 mm sieve is submerged in water so that the screen has 1 or 2 cm on it. Then 100 g of bulk soil is poured into this sieve and left for 5 minutes to soak. After 5 minutes of soaking the sieve is wash with an up and down motion in and out of the water about 50 times in 2 minutes. The sieve is again rinsed gently from the side with distilled water. The soil retained on 2 mm aggregate is then set aside to be capture and dried later. The water and soil that passed through 2 mm are poured into 0.25 mm sieve. Enough water is added to cover the sieve and soil and this next smaller sample aggregate is wash out of the soil using the same procedure above. This fraction is also allowed to set aside. Materials that were retained on both the sieve were empty into a 250 ml beaker and filter through a filter paper to remove the water, transferred into a weighted aluminum pan, oven dried at 100°C and weighed again after drying. The same process is repeated for the soil fraction that passed through the 0.25 mm sieve. Then

$$\%\text{ retained and passed in each fraction} = \frac{\text{Net weight}}{\text{original weight taken in the beginning}} \tag{8.4}$$

The mean weighted diameter (MWD) of the aggregates was calculated by multiplying the proportion of soil in each of the three class by the mid-point of the respective sieve size class(Saygin et al., 2017)

8.2.4 Plant height data

Height of the plant were measured using a measuring tape at maturity. The mean height of the plants collected from each treatment were determined using the formula:

$$\text{Mean height of the plant per plot} = \frac{\text{sum of height of plants per treatment}}{\text{number of plants per treatment}} \tag{8.5}$$

8.3 Results and Discussion

8.3.1 Soil characteristics prior to the experiment

The initial physiochemical composition of the soil used in the study prior to the commencement of the experiment is shown in Table 8.1.The initial soil properties was more or less similar in all the three plot. The pH of the soils in all the three plots was initially found to be acidic (Table 8.1). Most of the soils in Northeast India are predominantly acidic in nature because these areas are prone to heavy rainfall. Heavy rainfall washes away the bases elements such as calcium, magnesium from the soil and replaces the bases with acidic elements(Alloway, 2013; Dutta and Gokhale, 2017) .The texture of the soil was found to be silt loam. The bulk density of the three plot range from 1.31-1.33 (g/cm^3), EC from 0.52-0.57 (m mho cm^{-1}). The analysis showed that the soil of the study area as depleted in soil carbon, having low value of SOC (0.95 %). The large macro aggregate (> 2 mm) constituted around 40-45 % and the small macro-aggregate (0.25−2 mm) constituted around 47 % of the aggregate size.

8.3.2 Soil properties after treatment

After application of vermicompost enriched with biofertilizer for four consecutive growing seasons, there was a significant effect on the soil properties. Figure 8.2 shows the pH value of three treatments at various stages (season) of the experiments. At the end of the fourth stages of the experiment, the acidity of the soil was observed to be less in Field 2 and Field 3 compared to Field 1 respectively. It can be seen that the addition of vermicompost and biofertilizers tend to bring the acidity to normal but the shift in pH was found to be very small. Thus it can be concluded that the addition of vermicompost and biofertilizers was not the best choice to reduce the pH of acid soil, instead the use of lime as reported by many literatures(Cregan et al., 1989; Chimdi et al., 2012) may be the best choice to reduce the pH of acid soil in this type of soil.

Table 8.1: Initial properties of the soil used in the study

Treatment	**Parameters**							
	SOC (%)	pH	BD (g/cm^3)	EC (m mho cm^{-1})	Large macro aggregate (%)	Small macro aggregate (%)	Moisture content (%)	Textural class
Field 1	0.95	4.6	1.32	0.56	40	48	28.13	Silt loam
Field 2	0.94	4.6	1.310	0.52	43	47	26.95	Silt loam
Field 3	0.96	4.8	1.33	0.57	44	47	26.43	Silt loam

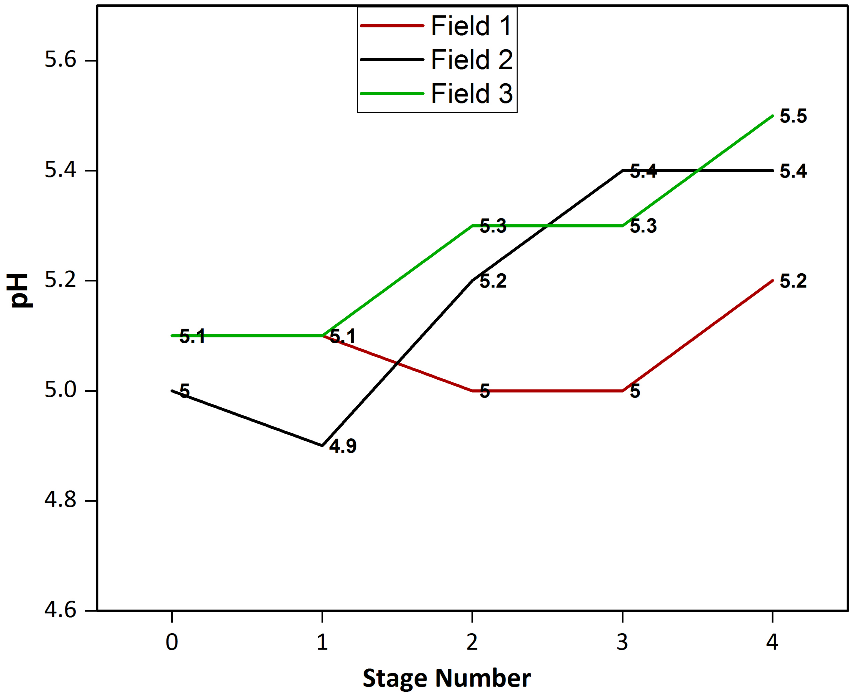


Figure 8.2: pH values from three field plots at various stages of the experiment.

The addition of vermicompost enriched with bio-fertilizers was observed to affect the soil organic carbon content of the soil. Figure 8.3 showed that the increase in SOC content is proportionate to the amount of vermicompost applied. The SOC content at the end of four Okra crop seasons increased by 5.26 % in Field 1, 144.68 % in Field 2 and 202.08 % in Field 3 as compared to the baseline period. A small increase in carbon content of Field 1 may come from the plant residues which were chopped and buried at the end of each experiment, while in case of Field 2 and Field 3, besides the soil carbon accumulated from crop residue, the additional accumulate carbon was derived from organic materials present in the compost (Diacono and Montemurro, 2011).

The addition of vermicompost enriched with bio-fertilizer decreased the value of bulk density by the end of the experiment. The lowest mean bulk density was observed in the field where the most doses of fertilizers were added (Figure 8.4). The increasing rate of vermicompost from 1.5 t ha-1 to 3.5 t ha-1 along with biofertilizers led to

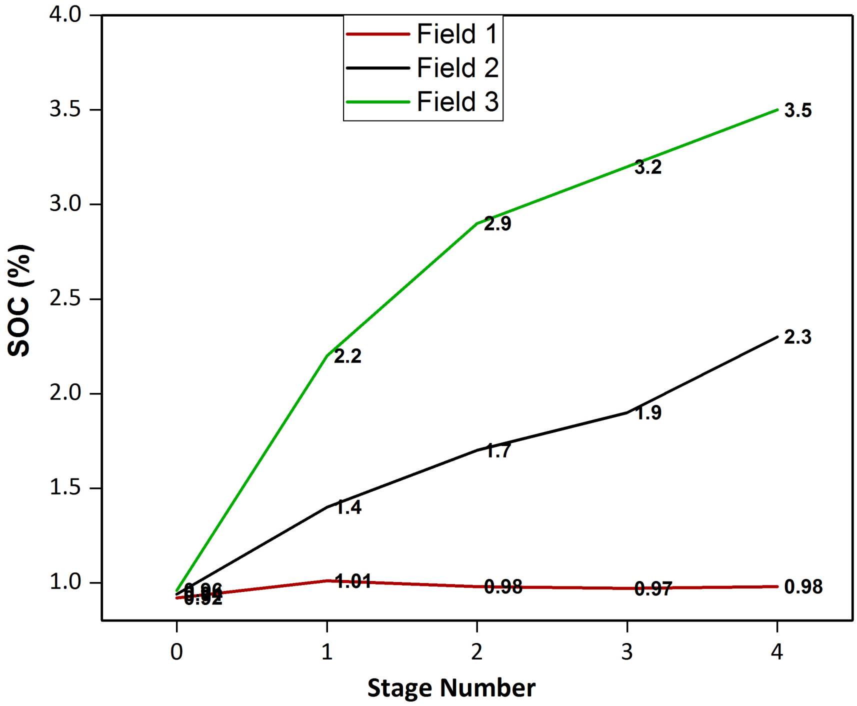


Figure 8.3: Soil carbon values from three field plots at various stages of the experiment.

the decreased in bulk density of filed 2 and field 3 by 4.5% and 6.1% as compared to field 1. A similar effect of vermicompost and organic waste on bulk density was also reported by other researchers (Blanco-Canqui and Lal, 2004; Srivastava et al., 2016) . The reduction of the bulk density of the soil on adding of compost may be due to the low particle density of these compost which when blended with the minerals fraction of the soil improves the soil aggregation and porosity (MacRae and Mehuys, 1985).

Determination of electrical conductivity (EC) was carried out to measure the amount of total soluble salts present in the soil samples (expressed in m mho cm^{-1}). EC was found to be significantly higher in field 2 and field 3 compared to field 1 (Figure 8.5), except during the first phase of the crop cycle, where EC in field 2 was found to be similar to field 1. However, in field 2, an increase in EC was observed with an increased number of the crop cycle. Such observation was also reported by Niklasch and Joergensen (2001); Sarwar et al. (2003)). EC of the soil was reported to improve with the addition of compost or manure irrespective whether the soil is alkaline or acidic (Sarwar et al., 2003).

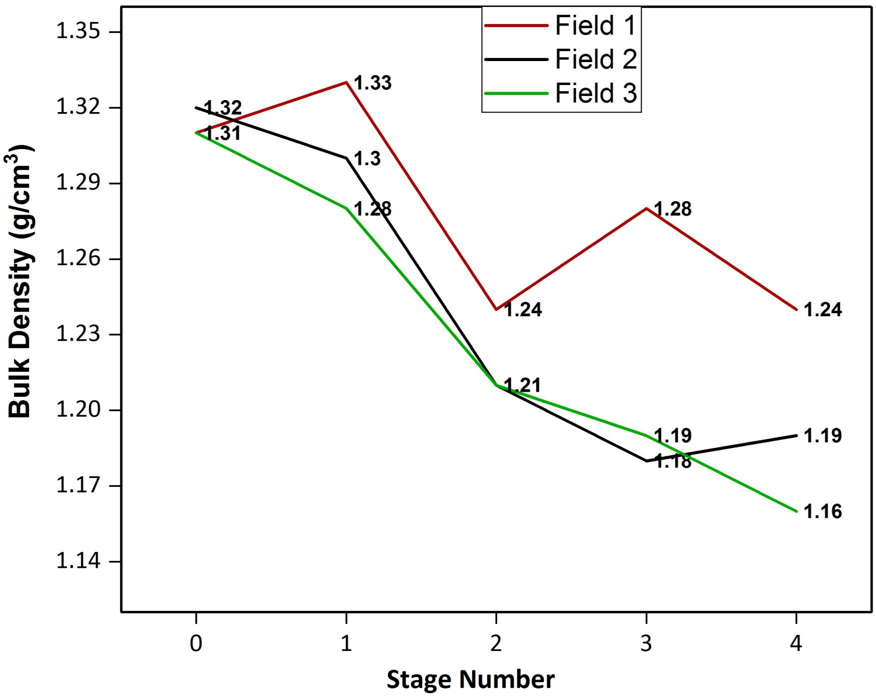


Figure 8.4: Bulk density values from three field plots at various stages of the experiment.

8.3.3 Effect of treatments on aggregate size distribution

Soil aggregation significantly changes with the application of vermicompost enriched with bio-fertilizer. As shown in Figure 8.6, in field 1(Control unfertilized plot) there was no significant difference in the aggregate size distribution in the four stages of the growing season of okra crop. However, a significant increase in the amount of large macro-aggregate and decreased in the proportion of small macro-aggregate were observed in field 2 and field 3 as compared to field 1 during the four stages of Okra crop. This implies that the application of vermicompost enriched with biofertilizers could significantly enhance the soil structure. Nonetheless, there was no significant difference

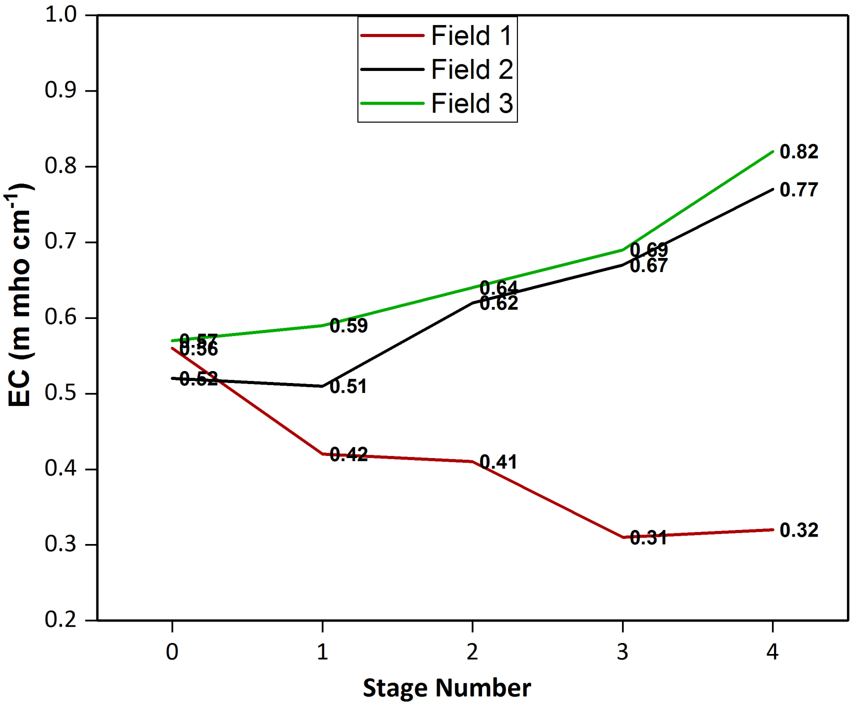


Figure 8.5: Electrical conductivity values from three field plots at various stages of the experiment.

observed in aggregate size distribution between field 2 and field 3. This increase in large macroaggregate in field 2 and 3, maybe the addition of vermicompost (a decomposed organic biomass) enriched with biofertilizer acts as a good cementing agent which bind together the small macroaggregate into a large macroaggregate and ultimately improves the soil structures. A similar result was reported by Ouni et al. (2014); Liu et al. (2019) who reported that vermicompost released organo-mineral complex like exopolysaccharides when added into the soil, which acts as a binding material for aggregate. The mean weight diameter of aggregate size distribution was also found to increase significantly in field 2 and field 3 in comparison to Field 1 (Figure 8.7). When SOC, bulk density and Mean weight diameter were considered (Figure 8.8), it was observed that SOC could explain most of the variability of MWD and bulk density in Field 2 and 3. SOC showed a linear and positive correlation with mean weight diameter and on the other hand a negative correlation with soil bulk density. This indicates that ap-

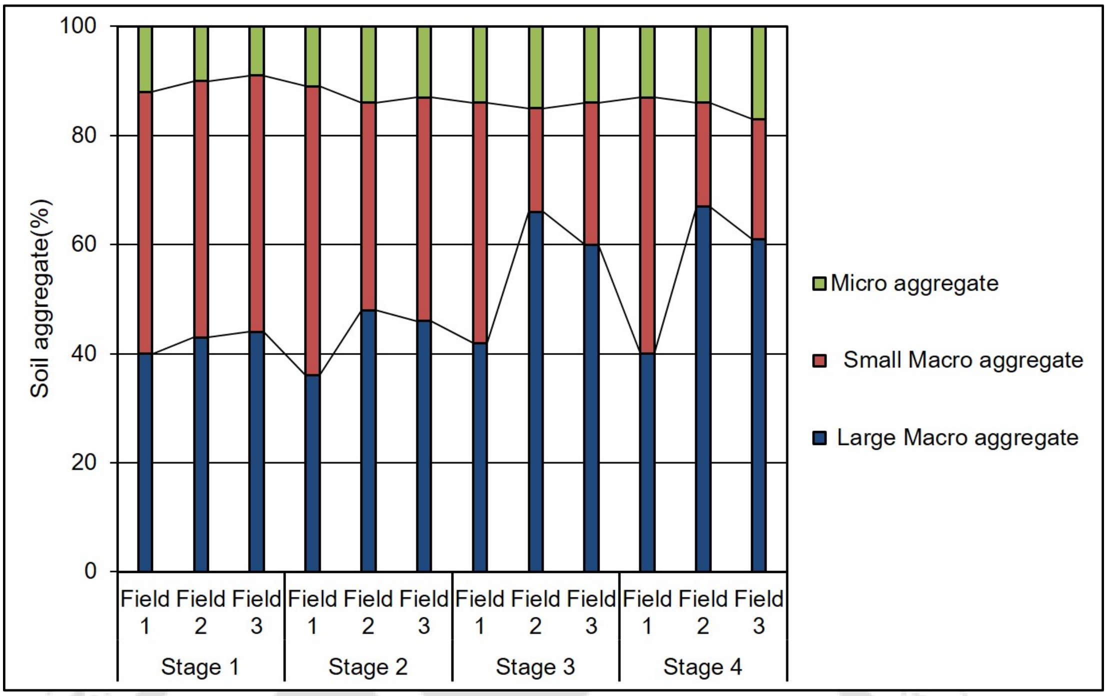


Figure 8.6: Effect of application of vermicompost enriched with bio-fertilizer on the distribution of soil aggregate at 0-20 cm of Okra cropping system.

plication of vermicompost enriched with biofertilizer increased the soil carbon which in turn improves the soil aggregation and consequently leading to an increase of large macro-aggregate and conversely reduce the bulk density of the soil. This information signifies the important role of SOC for improving soil structure and soil quality.

8.3.4 Effect of treatment on plant height

In agreement with the finding of Ofosu-Anim et al. (2006)), application of vermicompost enriched with bio fertilizers was found to significantly increased the height of okra crop. However, no significant difference was found between the height of Okra crop in Field 2 and Field 3(Table 8.2). This is an agreement with the finding of Uwah et al. (2010) who reported that Okra crop does not require large amount of fertilizers for optimum growth. However this result is in disagreement with the finding of (Amanullah et al., 2010) who stated that application of manure will not only supply nutrients to the crop but will affect its height and yield respectively.

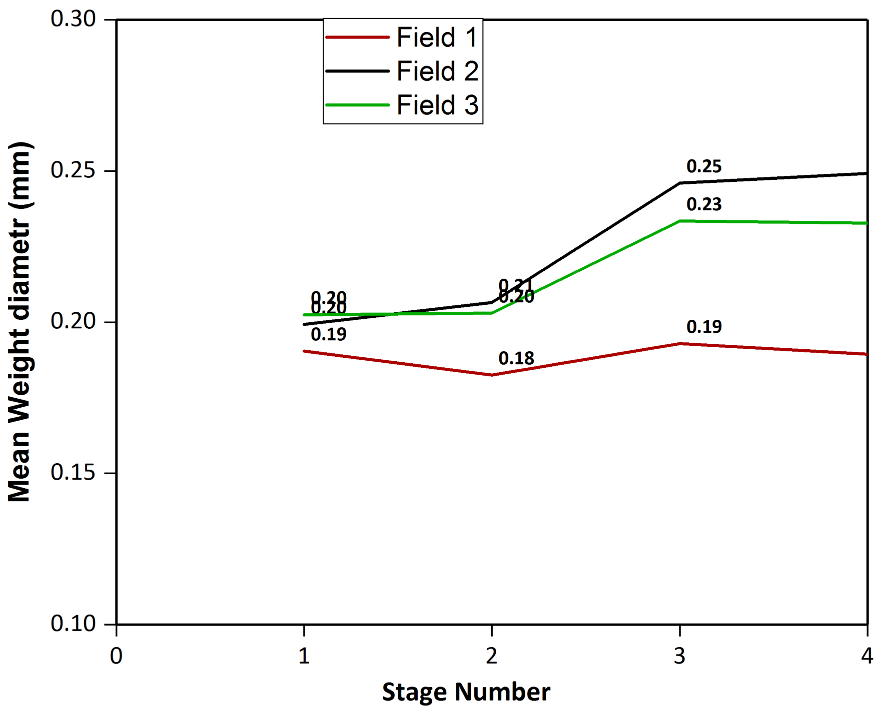


Figure 8.7: Effect of application of vermicompost enriched with bio-fertilizer on the mean diameter of soil aggregate at 0-20 cm of Okra cropping system.

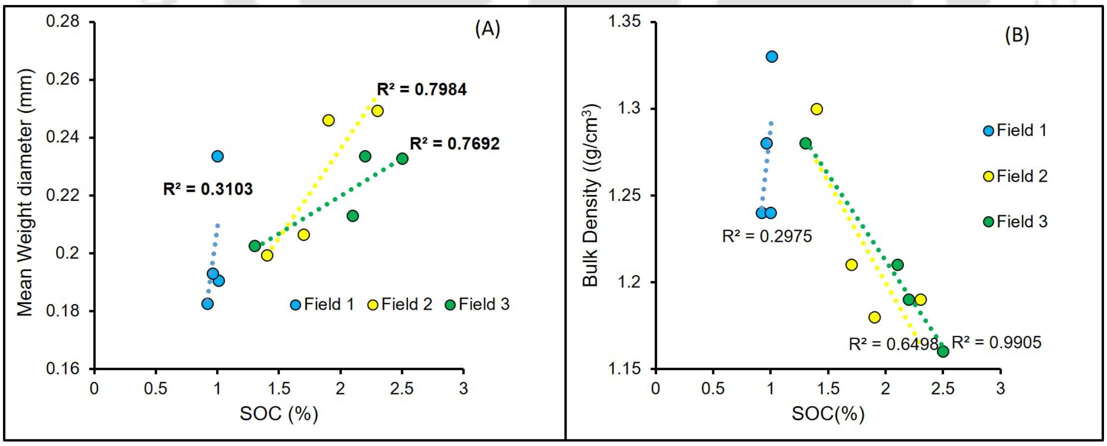


Figure 8.8: Relationships between (A) soil organic C (SOC) concentration and mean weight diameter (MWD) of water-stable aggregates and (B) soil organic C (SOC) concentration and Bulk density (g/cm^3) in all treatments.

Table 8.2: Height (m) of okra at maturity

Treatment	Mean plant height (m)			
	Season1	**Season 2**	**Season 3**	**Season 4**
Field 1	0.58^b	0.54^b	0.49^b	0.50^b
Field 2	0.70^a	0.71^a	0.73^a	0.74^a
Field 3	0.72^a	0.70^a	0.72^a	0.75^a

*Means in the same column with same letters are not significantly different ($P<0.05$)

8.4 Conclusion

Application of vermicompost enriched with biofertilizer for four consecutive growing seasons of Okra crop improved soil macro-aggregation, soil physical and chemical properties, soil aggregate stability (as indicated by mean weight diameter) and could have explained the improvement of plant height. At the end of the experiment, soil organic carbon showed a positive correlation with mean weight diameter and on the other hand a negative correlation with soil bulk density, indicating that application of vermicompost enriched with biofertilizer improves soil carbon which in turn improves the soil structure The underlying mechanism behind these beneficial effects could be because of the fact that vermicompost are suitable carrier of free-living nitrogen-fixing bacteria (Azobacter). Thus a combination of vermicompost with biofertilizers improves the soil health and improves the absorption of the important nutrients necessary for the growth of Okra crop.

CHAPTER 9

Conclusions and recommendations for the future work

9.1 Overview

The present study presents a detailed assessment of soil organic carbon, dealing with its occurrence, distribution, resilience and its dependence on natural and anthropogenic factors. To accomplish the above objectives,the study first developed a predictive model for finding a relationship between known soil carbon values and environmental variables so that soil carbon can be map digitally. This enables us to identify the potential regions for soil carbon storage as well as in evaluating the most influencing factors in the determination of carbon storage. Knowing the factors that influence the soil carbon storage, the study evaluates the effect of various anthropogenic activities Viz. land use conversion and land management on carbon fluxes as well as on overall soil quality. An integrated tool in the form of soil quality index was developed to enable monitoring the effect of various land management on soil carbon and soil quality as a whole. On-farm experiment was also conducted to evaluate the effect of land management on SOC and soil properties. The study also evaluates the effect of natural factors (climatic variables) in controlling the amount of soil carbon and made an attempt to understand how likely changes in climatic variables will have an impact on soil carbon. Based on the selected objectives, following are the conclusive points notified in the overall study:

9.2 Digital Mapping of Soil Organic Carbon

A time and cost saving method Viz. digital mapping approach was used in attempt to model the distribution of soil carbon stock in order to predict and generate continuous spatially explicit soil carbon map in Northeast India. Firstly, negative exponential depth function has been used to fit the vertical distribution of soil carbon data, and then Random Forest model has been trained and tuned to predict the parameters of the exponential function using climate data and satellite images. The obtained parameters were finally interpolated using ordinary Kriging method and spatial distribution map across the study area has been generated.

The findings from this objective indicated good results for the application of this technique to predict SOC stock even with less ground data for the mountainous and less accessible area of NE India. The results from the study also enhance our knowledge over the role of land use on SOC storage in the study area, thus denoting the potential opportunities to use land management as a ways to improve the SOC storage of this region. Information from this study can be also useful for identification of potential regions for soil carbon sequestration. It can help the policy makers in management and monitoring of natural resources and can serve as an input for further research-based modeling and simulation studies.

9.3 Effect of elevation gain on soil organic carbon

In this objective, a field study was carried out in three altitude zones along the forest stand of Meghalaya to examined the direct effect of elevation on SOC versus its indirect effect on SOC mediated by climate, soil and vegetation parameters.

Here, we found that there was no direct relationship between elevation and SOC storage in the study area. Instead, the study found that elevation had a direct positive effect on precipitation and soil moisture and direct negative effect on temperature. Climate favorability especially higher precipitation and low temperature, as well as high soil moisture level along the elevation gradients, were in turn found to associated with higher plant species richness and plant density, which had a positive effect on SOC storage, thus representing the influence of elevation on SOC.

The results of this finding have an essential implication for environmental management and for improving the existing carbon cycle model: planting and conservation of high plant species richness suitable for an area can help to improve soil carbon sequestration which will improve soil fertility as well as in mitigating the global warming.

9.4 Carbon fluxes from land use and land management

Analyses of the changes in carbon storage as a result of anthropogenic activities Viz. land use conversion and land management during a period of 2006 to 2013 in the states of Assam, Meghalaya, Manipur, Nagaland and Tripura in NE India was carried out. Land use map from 2006 -2013 used for the analysis were obtained from National Remote Sensing Center (NRSC) Hyderabad, in digital format on request. Data about various land use management activities were obtained from statistical year book of India. To estimate the change in biomass carbon stock, stock difference method as defined by IPCC was followed using country regional specific data. For calculation of SOC stock, methodology used was based on the difference of SOC stock between different land use categories.

Results indicated an increase in settlement areas and agricultural areas at the expenses of forest areas and other land use cover. However, the extent of various land use varies from state to state. Whereas Assam, Manipur and Tripura experienced a net accumulation of soil organic carbon (SOC) as a result of land use conversion by an amount of approximately 3.91, 0.22, 0.13 TgC, SOC declined in Meghalaya and Nagaland approximately by an amount 0.11 and 0.62 TgC. Assam, Manipur, Meghalaya and Nagaland experienced a net decrease in carbon biomass between 2006 to 2013 by an amount of approximately 0.43, 1.51, 0.31 and 0.49 TgC, however Tripura experienced a net accumulation of carbon biomass approximately by 0.12 TgC.

The outcomes of this study signifies that land use conversion and land management in NE India are moving towards the opposite direction of carbon reduction. The main reasons can be attributed to the decrease in forest land to meet the demand for carbon absorption, improper grassland and agricultural land management and rapid expansion of settlement areas. With more changes in land use expected to occur in the future and land use are often neglected in the land use land management planning, results of the study stress that the government and land use planner of this region must include carbon emission in their future land use planning to help in mitigation of carbon emission and to slow down the changing climate in the coming decades.

9.5 Framework for soil quality assessment

To make a sound decision in selection of suitable land use and land management, understanding of how soils respond to different land use and management scenarios is essential. A soil quality index (SQI) was therefore developed to assess the effect of various agricultural managements that are currently practices in Northeast India (NE) on selected physical, chemical and biological soil properties.

Five land use and soil management systems (LUSM) Viz. 1) dense forest 2) pine forest 3) terrace/bun agricultural system 4) shifting/jhum cultivation and 4) abandoned land after shifting cultivation were selected for evaluation of soil quality. The overall soil quality index of these different LUSM were analysed and compared. The study also identify the most suitable soil quality indicators in defining the soil quality. Ninety three soil samples were assemble and analyzed for different soil quality indicators. For selection of indicators, the collected soil samples were subjected to principal component analysis, followed by Varimax rotation algorithm. Subsequently, selected indicators were transformed and assigned a score based on linear scoring function.

Significant ($P < 0.05$) variations in soil quality were found across different land use. The overall soil quality index was found to follow the following orders: 0.91 (Dense forest) > 0.69 (Shifting cultivation) > 0.63 (Pine forest)> 0.57 (Bun cultivation) > 0.37 (Abandoned after shifting cultivation). Thus the quality of soils was observed to be highly influenced by land use types. Results also denote that shifting cultivation is one of the factors responsible for degrading the soil quality of the study area. Soil organic carbon was observed to be the powerful indicators of soil quality. The method used in this study proved to be sensitive to evaluate the soil quality and demonstrated that carbon management hold the key for improving the soil quality of the study area.

9.6 Carbon stock and its associated resilience capacity

All the above analysis were carried out at the state level (Northeast India) and regional level. However, for this objective, an attempt was made to carry out on all India basis by dividing the entire country based on Agro-climatic zone.The motivation of this objective is to understand the relationship between SOC and climatic variables within each agro-climatic regions of India.

Using copula theory, the present study focus investigate the soil carbon dynamics and the likelihood of occurrence of SOC under varying climatic conditions across the 14 agro-climatic zones of India. Results demonstrate the likelihood of occurrence of SOC under both low and high temperature/precipitation conditions. Results indicate that SOC of agro-climatic zones situated in semi-arid and arid regions are more sensitive to changes in climatic variables compared to that of the others.

In this objective, we also quantify the soil resilience of the agro-climatic zones based on the amount of SOC content. Results showed that only 1/3 of agro-climatic zones of India were found to be resilient during the study period (1985-2005).

Thus findings from the study facilitate the identification of the most sensitive agro-climatic zone of India for soil carbon management and climate-related policy. It stresses the need for identifying site-specific management practices that can facilitate soil health and improve the soil resilient capacity of the country for food security and environmental management.

9.7 Soil organic carbon and soil aggregation enhancement from vermicompost management enriched with biofertilizers

In this objective a field experiment was undertaken to investigate the effect of microbial enrichment on vermicompost on mean weight diameter of aggregate, distribution of aggregate, soil physical and chemical properties and on crop parameters.

Results of the experiment indicates that the application of vermicompost enriched with biofertilizer improves the plant height and the soil properties, particularly SOC. Significance increase in the amount of large macro-aggregate and decreased in the proportion of small macro-aggregate were observed in plot with treatments as compared to unfertilized plot during the experiment. Mean weight diameter(MWD) was also observed to significantly improves as compared by the end of the experiment as a result of treatments.Thus it was found that addition of vermicompost enriched with biofertilizers increased the soil carbon which in turn improves the soil aggregation and consequently leading to increase of large macro-aggregate and conversely reduce the bulk density of the soil.

9.8 Major contributions of the thesis

The major contributions of this thesis can be summarized as follows:

- A model was developed to map soil organic carbon of Northeast India digitally as a function of land use, climate, topography and vegetation.
- An integrated tool in the form of soil quality index was developed to enable monitoring the effect of various land management on soil carbon and soil quality as a whole.
- The extent to which the soil and vegetation of four states of Northeast India act as a source or sink to atmospheric carbon as a result of shifts in land use in the past decade has been analyzed.
- Finding of the study proves that vermicompost are suitable carrier of free-living nitrogen fixing bacteria which when added together helps to improve the soil health in terms of soil physical and chemical properties.
- Our findings have important implications for improving global carbon cycling models and ecosystem management: Maintaining high levels of plant diversity can enhance soil carbon sequestration.

9.9 Recommendation for future scope

Based on the outcome of this thesis work, this section provides some of the possible future directions for research:

- Soil quality indexing for soil under five land use and soil management systems was carried out. However, the study was conducted with limited data for financial constraints. Therefore, it will be necessary to extend this research with more data and land use systems. It will also be important to correlate the soil quality indices with crop yields and other ecosystem services at different climatic and soil conditions.
- A field experiment was conducted to evaluate the effect of the application of vermicompost enriched with biofertilizers on soil carbon and other soil properties. This

study must be extended on a large scale field experiment involving the farmers because ultimately they will be the one who will implement these on the fields.

- Results of the study showed that shifting cultivation which is still prevalent in Northeast India contributes significantly to forest loss and is the main source of soil quality degradation. Therefore, efforts must be made to restore the quality of abandoned land after shifting cultivations. It will be of paramount importance to collect baseline data at this initial time to evaluate the impacts of these efforts in terms of carbon sequestration, agricultural productivity and other ecosystem services.

- Study the role of soil microbes in the global carbon cycle and identify the microorganisms responsible for the processing of plant photosynthetic carbon inputs to soil in a wide range of soils.

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Appendix A

Table A1: Information of the soil properties of 218 sites extracted from National Bureau of Soil Survey and Landuse Planning

Lat	Long	Sand (%)	Clay (%)	Silt (%)	SOC (%)	Soil type	Soil depth (cm)
29.84	95.33	71.5	7.5	21.0	1.61	Sandy loam	18
27.98	94.20	70.8	14.6	14.6	2.25	Sandy loam	18
27.49	95.35	44.0	26.0	30.0	2.33	Loam	18
27.36	94.97	1.2	55.0	43.8	2.38	Silty clay	12
27.36	95.86	25.2	29.5	45.3	1.50	Clay loam	13
27.28	94.79	19.4	32.0	48.6	1.76	Silty clay loam	15
27.18	94.98	51.5	14.4	34.1	1.70	Loam	14
27.16	93.86	17.8	24.5	57.7	0.90	Silt Loam	13
27.10	94.40	36.0	11.3	52.7	1.72	Silt Loam	20
27.09	93.61	8.5	43.7	47.8	2.30	Silty clay	19
27.04	94.26	50.0	14.0	36.0	1.94	Loam	31
27.04	94.35	53.0	6.9	40.1	2.15	Sandy loam	15
27.02	89.83	31.5	32.5	36.0	1.19	Clay loam	13
27.00	94.84	30.5	32.5	37.0	0.80	Clay loam	21
26.97	94.90	50.5	24.5	25.0	0.60	Sandy clay loam	22
26.94	94.78	15.2	20.2	64.6	1.30	Silt Loam	13
26.92	94.63	9.7	58.8	31.5	2.60	Clay	15
26.89	93.47	36.1	29.2	34.7	1.12	Clay loam	24
26.88	93.76	39.3	15.0	45.7	0.86	Loam	13
26.84	93.06	30.0	35.1	34.9	1.10	Clay loam	15
26.83	94.11	78.0	9.2	12.8	1.38	Sandy loam	11
26.83	92.72	36.0	32.0	32.0	1.15	Clay loam	11
26.80	94.18	72.3	12.7	15.0	0.63	Sandy loam	13
26.80	94.43	33.0	10.8	56.2	0.99	Silt Loam	11

26.79	94.23	16.8	22.2	61.0	1.24	Silt Loam	14
26.78	94.13	30.0	23.5	46.5	0.90	Loam	16
26.77	95.17	15.2	38.5	46.3	2.00	Silty clay loam	16
26.75	91.36	18.5	35.0	46.5	1.42	Silty clay loam	20
26.74	94.10	70.5	14.7	14.8	0.95	Sandy loam	18
26.73	95.09	30.1	36.0	33.9	1.53	Clay loam	14
26.70	94.28	60.5	18.2	21.3	1.15	Sandy loam	18
26.70	93.43	10.1	29.2	60.7	0.54	Silty clay loam	14
26.70	94.26	71.4	8.2	20.4	0.62	Sandy loam	21
26.68	94.09	22.9	25.1	52.0	1.26	Silt Loam	13
26.65	94.15	22.9	24.4	52.7	0.88	Silt Loam	20
26.65	94.83	14.3	44.0	41.7	3.33	Silty clay loam	19
26.64	94.39	66.1	11.5	22.4	0.54	Sandy loam	14
26.63	93.89	2.4	36.5	61.1	1.52	Silty clay loam	20
26.63	91.83	43.0	28.0	29.0	1.04	Clay loam	28
26.61	94.37	16.9	27.3	55.8	0.77	Silty clay loam	14
26.60	94.35	67.5	18.2	14.3	0.78	Sandy loam	20
26.60	94.26	60.5	13.0	26.5	0.72	Sandy loam	15
26.59	93.37	4.4	49.5	46.1	1.10	Silty clay	16
26.59	94.35	67.0	14.4	18.6	0.66	Sandy loam	29
26.57	94.75	16.3	43.5	40.2	2.19	Silty clay	20
26.55	92.97	29.7	27.0	43.3	0.98	Clay loam	15
26.55	92.39	70.0	16.9	13.1	0.58	Sandy loam	7
26.54	91.26	36.0	31.0	33.0	0.83	Sandy clay loam	14
26.52	91.09	39.5	30.3	30.2	1.50	Clay loam	18
26.50	92.67	86.6	10.3	3.1	1.60	Loamy sand	19
26.50	94.15	62.0	24.5	13.5	2.13	Sandy clay loam	19
26.47	90.51	79.2	12.8	8.0	0.99	Sandy loam	18
26.47	94.88	7.4	32.0	60.6	1.51	Silty clay loam	23
26.45	93.93	31.0	40.6	28.4	1.25	Clay	17
26.45	94.18	38.5	25.5	36.0	1.58	Loam	15

26.44	91.24	18.0	34.8	47.2	1.10	Clay loam	11
26.43	92.36	22.4	26.5	51.1	0.80	Silt Loam	9
26.39	94.81	18.7	42.5	38.8	2.30	Clay	19
26.39	92.36	64.7	20.0	15.3	0.90	Sandy clay loam	10
26.37	94.98	3.9	38.5	57.6	1.84	Silty clay loam	10
26.37	90.97	45.3	28.4	26.3	0.59	Silty clay loam	21
26.37	90.60	64.5	18.5	17.0	0.91	Sandy loam	20
26.36	93.86	27.1	27.5	45.4	1.21	Clay loam	22
26.34	92.30	36.0	30.5	33.5	1.90	Clay loam	6
26.34	93.83	58.5	17.0	24.5	1.23	Sandy loam	13
26.33	92.68	61.8	26.7	11.5	1.90	Sandy clay loam	16
26.33	94.37	5.1	39.5	55.4	0.40	Silty clay loam	19
26.32	92.32	47.4	19.0	33.6	1.00	Loam	10
26.32	93.50	76.6	14.3	9.1	0.97	Sandy loam	15
26.31	92.46	53.9	16.0	30.1	0.90	Sandy loam	10
26.30	92.31	29.1	32.5	38.4	1.40	Clay loam	15
26.30	93.79	52.9	28.0	19.1	0.98	Sandy clay loam	23
26.30	94.07	9.3	27.0	63.7	1.33	Silty clay loam	22
26.28	91.33	29.4	30.1	40.5	1.20	Clay loam	15
26.27	94.46	44.2	21.0	34.8	1.70	Loam	20
26.27	94.17	51.2	13.5	35.3	1.36	Loam	19
26.26	91.01	36.0	37.0	27.0	1.03	Clay loam	20
26.25	90.31	66.0	16.0	18.0	2.08	Sandy loam	30
26.25	92.05	5.8	17.0	77.2	0.90	Silt Loam	12
26.25	92.78	46.6	21.0	32.4	1.10	Loam	19
26.24	92.38	37.2	43.5	19.3	1.90	Clay	10
26.23	94.39	9.0	34.5	56.5	2.94	Silty clay loam	18
26.23	92.50	78.5	12.5	9.0	1.52	Sandy loam	16
26.20	93.81	5.7	33.0	61.3	1.18	Silty clay loam	17
26.19	94.17	58.6	23.5	17.9	1.28	Sandy clay loam	16
26.17	92.40	8.2	73.0	18.8	1.60	Clay	10

26.15	92.75	25.0	24.5	50.5	0.98	Silt Loam	15
26.14	91.57	82.0	4.8	13.2	0.78	Loamy sand	15
26.12	92.28	31.1	21.0	47.9	1.20	Loam	12
26.10	92.27	3.4	35.6	61.0	2.10	Silty clay loam	16
26.09	91.55	68.1	11.2	20.7	1.64	Sandy loam	15
26.07	93.56	59.5	7.7	32.8	1.04	Sandy loam	22
26.07	94.43	6.4	48.0	45.6	1.98	Silty clay	15
26.06	91.60	71.7	12.2	16.1	0.84	Sandy loam	19
26.04	94.13	18.7	28.0	53.3	1.33	Silty clay loam	14
26.04	91.05	16.0	53.8	30.2	1.82	Clay	14
26.04	91.08	47.5	32.6	19.9	1.04	Sandy clay loam	14
26.03	90.31	24.5	27.0	48.5	1.76	Clay loam	12
26.01	90.00	77.0	13.0	10.0	1.56	Sandy loam	16
25.98	90.80	35.5	19.0	45.5	0.91	Loam	16
25.98	90.80	69.8	21.5	8.7	0.72	Sandy clay loam	15
25.97	90.15	31.1	25.4	43.5	1.18	Loam	22
25.95	91.08	21.0	26.4	52.6	0.47	Silt Loam	17
25.95	91.18	50.0	19.2	30.8	0.78	Loam	15
25.94	90.90	42.6	22.0	35.4	1.27	Loam	22
25.93	90.78	43.9	20.8	35.3	1.42	Loam	26
25.93	91.08	49.6	13.9	36.5	1.38	Loam	14
25.92	90.75	10.8	26.5	62.7	1.42	Silt Loam	20
25.91	91.24	75.0	8.2	16.8	0.85	Sandy loam	20
25.91	93.76	47.5	18.0	34.5	0.94	Loam	22
25.88	90.13	27.5	30.6	41.9	1.28	Clay loam	25
25.88	91.05	52.5	18.2	29.3	1.80	Sandy loam	15
25.87	90.05	16.5	40.0	43.5	1.34	Silty clay	14
25.86	91.16	41.0	23.5	35.5	1.27	Loam	15
25.85	91.88	41.2	24.7	34.1	2.16	Loam	18
25.83	94.72	11.8	31.5	56.7	3.78	Silty clay loam	17
25.78	94.41	18.2	42.5	39.3	2.01	Clay	16

25.78	94.30	32.6	39.0	28.4	2.85	Clay loam	15
25.78	93.63	7.1	33.0	59.9	1.44	Silty clay loam	15
25.78	94.08	33.9	35.0	31.1	2.17	Clay loam	20
25.78	93.88	22.1	39.0	38.9	1.86	Clay loam	16
25.78	93.87	48.9	29.0	22.1	4.50	Sandy clay loam	20
25.75	93.98	13.1	33.5	53.4	2.99	Silty clay loam	20
25.75	91.85	31.5	28.5	40.0	2.90	Clay loam	12
25.74	93.98	25.5	32.0	42.5	2.73	Clay loam	18
25.73	94.80	26.4	39.0	34.6	3.08	Clay loam	18
25.73	94.13	15.0	39.5	45.5	2.50	Silty clay loam	16
25.73	94.24	14.7	48.0	37.3	1.95	Clay	17
25.73	93.89	43.3	23.0	33.7	1.14	Loam	26
25.72	93.13	74.7	10.0	15.3	0.53	Sandy loam	22
25.70	89.93	4.2	47.5	48.3	1.34	Silty clay	13
25.70	93.65	52.8	19.5	27.7	1.11	Sandy loam	13
25.68	94.05	18.7	42.5	38.8	1.60	Clay	16
25.67	91.73	62.3	16.5	21.2	0.78	Sandy loam	13
25.62	94.28	14.7	37.0	48.3	3.88	Silty clay loam	15
25.60	93.21	37.9	26.0	36.1	1.64	Loam	8
25.60	90.23	69.8	7.0	23.2	1.60	Sandy loam	16
25.58	92.45	16.9	25.5	57.6	3.12	Silt Loam	16
25.58	93.92	12.0	33.5	54.5	2.50	Silty clay loam	10
25.57	91.10	55.7	27.4	16.9	3.28	Sandy clay loam	15
25.55	90.83	24.6	43.7	31.7	1.70	Clay	20
25.55	91.63	20.4	23.1	56.5	2.22	Silt Loam	18
25.55	90.12	19.0	31.5	49.5	4.64	Silty clay loam	19
25.53	94.60	32.6	34.5	32.9	1.22	Clay loam	25
25.53	90.58	42.7	8.8	48.5	1.30	Loam	13
25.53	93.52	41.6	32.5	25.9	1.70	Clay loam	20
25.50	91.28	26.0	28.2	45.8	2.53	Clay loam	10
25.50	90.25	52.2	21.4	26.4	1.80	Sandy clay loam	9

25.50	93.58	56.4	26.0	17.6	1.36	Sandy clay loam	19
25.50	94.27	20.0	32.9	47.1	1.37	Silty clay loam	18
25.48	91.50	43.3	39.1	17.6	2.46	Clay loam	15
25.48	90.18	69.0	5.5	25.5	1.60	Sandy loam	18
25.48	90.23	69.5	15.9	14.6	0.60	Sandy loam	15
25.43	93.50	15.6	37.5	46.9	1.82	Silty clay loam	19
25.38	92.17	81.3	7.2	11.5	0.80	Loamy sand	14
25.38	91.45	68.1	2.5	29.4	1.28	Sandy loam	11
25.37	92.22	8.4	49.7	41.9	0.70	Silty clay	13
25.35	91.88	70.4	21.4	8.2	2.06	Sandy clay loam	23
25.32	93.22	5.1	41.0	53.9	2.14	Silty clay	21
25.30	91.88	52.3	16.0	31.8	4.08	Sandy loam	15
25.23	92.38	44.6	35.0	20.4	1.96	Clay loam	19
25.22	90.57	36.6	21.9	41.5	1.77	Loam	20
25.22	90.60	76.4	17.6	6.0	1.80	Sandy loam	18
25.22	91.97	71.5	12.7	15.8	1.70	Sandy loam	14
25.18	92.03	82.6	4.5	12.9	1.90	Loamy sand	19
25.13	93.08	16.6	39.0	44.4	3.00	Silty clay loam	20
25.05	93.51	44.2	21.0	34.8	1.71	Loam	12
24.93	91.27	55.2	24.7	20.1	0.70	Sandy clay loam	20
24.90	92.51	2.0	36.5	61.5	1.38	Silty clay loam	15
24.88	92.29	3.0	44.5	52.5	1.62	Silty clay	13
24.81	92.61	2.5	69.5	28.0	2.20	Clay	15
24.80	93.03	42.5	31.9	25.6	1.94	Clay loam	15
24.59	93.17	36.8	18.0	45.2	0.95	Loam	15
24.45	92.19	41.1	36.0	22.9	0.90	Clay loam	15
24.37	92.32	8.4	35.1	56.5	1.62	Silty clay loam	11
24.34	92.15	40.0	21.1	38.9	1.52	Loam	12
24.24	92.20	52.0	18.4	29.6	1.23	Loam	13
24.23	92.10	46.0	22.0	32.0	2.16	Loam	11
24.13	92.10	2.4	55.4	42.2	1.80	Silty clay	8

24.12	91.32	41.0	33.0	26.0	1.44	Clay loam	16
24.04	92.26	7.6	33.7	58.7	1.21	Silty clay loam	10
24.02	91.39	49.1	29.5	21.4	1.16	Sandy clay loam	16
24.02	91.63	8.8	34.6	56.6	1.71	Silty clay loam	14
24.02	91.71	53.8	22.0	24.2	1.20	Sandy clay loam	11
23.98	92.05	34.6	32.3	33.1	1.10	Clay loam	18
23.96	91.80	58.2	18.2	23.6	1.03	Sandy loam	17
23.95	92.02	67.2	18.9	13.9	0.64	Sandy loam	20
23.95	91.98	67.2	18.9	13.9	0.64	Sandy loam	13
23.93	92.27	36.6	21.9	41.5	1.80	Loam	10
23.93	92.28	23.0	37.9	39.1	1.10	Clay loam	21
23.93	91.91	16.0	37.2	46.8	1.90	Sandy clay loam	15
23.90	92.88	4.4	33.0	62.6	1.08	Silty clay loam	10
23.88	91.76	26.0	26.7	47.3	1.29	Loam	13
23.87	92.02	61.6	20.1	18.3	1.03	Sandy clay loam	11
23.85	91.92	63.2	24.1	12.7	0.80	Sandy clay loam	19
23.84	91.76	24.6	26.4	49.0	0.74	Loam	8
23.83	91.99	64.3	21.5	14.2	1.11	Sandy clay loam	11
23.82	92.00	58.9	23.0	18.1	1.62	Sandy clay loam	20
23.82	91.69	55.6	27.0	17.4	0.85	Sandy clay loam	10
23.80	91.34	55.6	25.3	19.1	0.80	Sandy clay loam	16
23.80	91.29	75.0	13.9	11.1	1.20	Sandy loam	5
23.80	91.58	1.8	65.5	32.7	2.43	Clay	10
23.79	91.29	37.0	40.9	22.1	2.80	Clay	12
23.78	91.85	60.0	23.1	16.9	1.09	Sandy clay loam	12
23.77	91.72	33.8	26.8	39.4	1.80	Loam	16
23.51	91.63	64.5	21.0	14.5	1.22	Sandy clay loam	7
23.50	91.74	41.0	32.0	27.0	1.30	Clay loam	11
23.50	91.43	58.0	25.3	16.7	1.28	Sandy clay loam	7
23.47	91.63	50.4	26.7	22.9	0.59	Sandy clay loam	24
23.43	91.30	67.0	19.3	13.7	0.41	Sandy loam	17

23.41	91.30	75.0	13.9	11.1	0.50	Sandy loam	13
23.36	92.17	60.0	21.3	18.7	1.28	Sandy clay loam	15
23.35	91.32	58.2	20.6	21.2	0.94	Sandy clay loam	20
23.28	91.60	53.6	20.5	25.9	1.07	Sandy clay loam	12
23.28	91.41	49.1	24.5	26.4	1.00	Sandy clay loam	12
23.26	91.60	58.0	25.9	16.1	1.00	Sandy clay loam	16
23.05	91.57	37.0	23.5	39.5	1.50	Loam	13
23.02	91.58	31.5	25.0	43.5	0.89	Loam	11

Appendix B

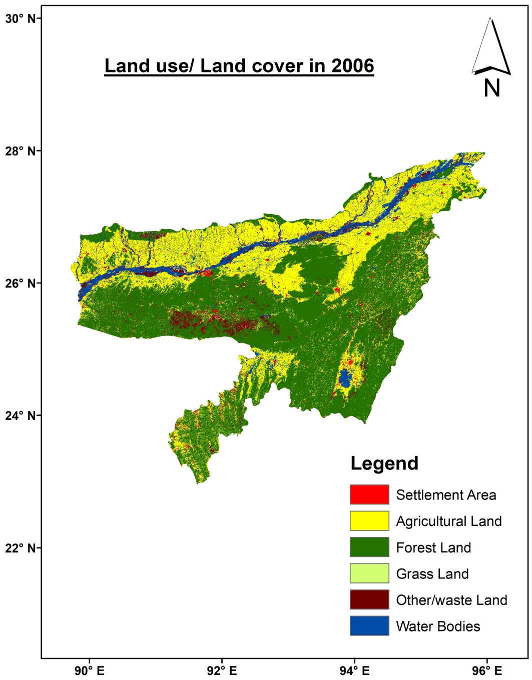

Figure A1: Landuse/Land cover in 2006

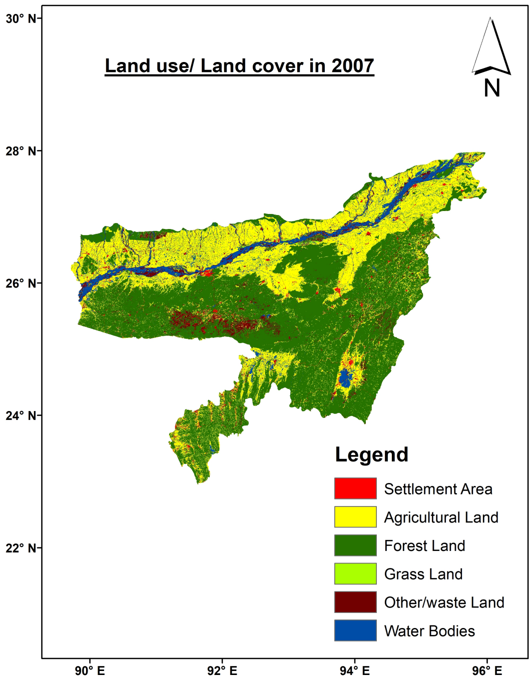

Figure A2: Landuse/Land cover in 2007

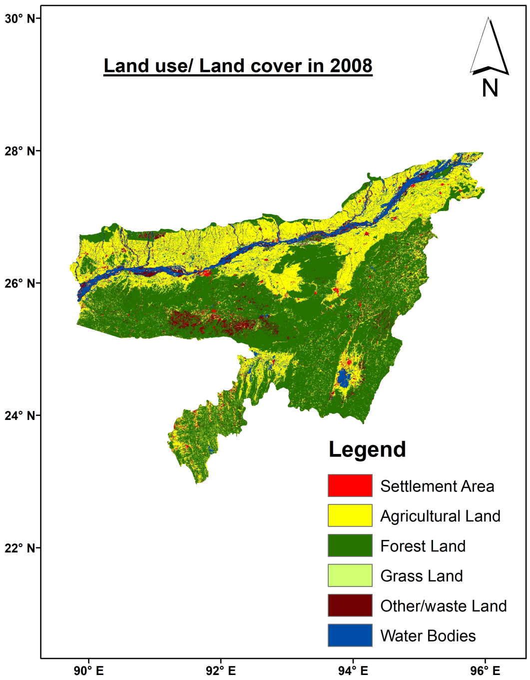

Figure A3: Landuse/Land cover in 2008

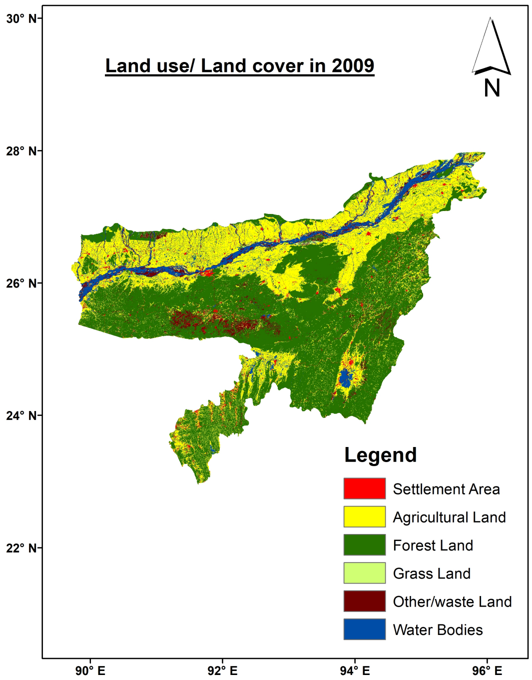

Figure A4: Landuse/Land cover in 2009

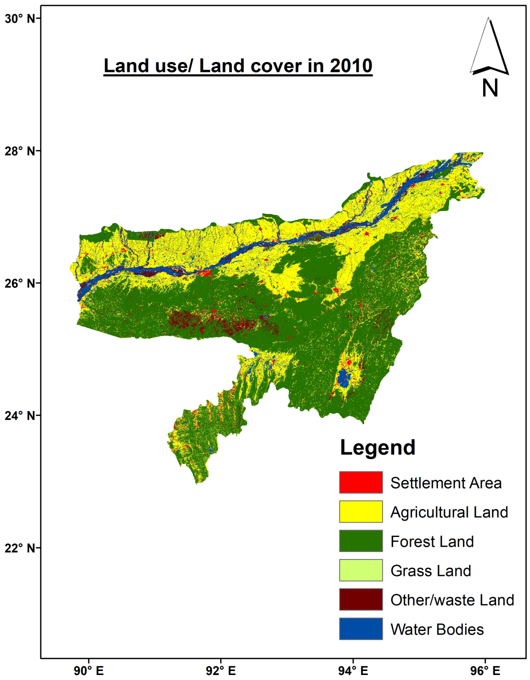

Figure A5: Landuse/Land cover in 2010

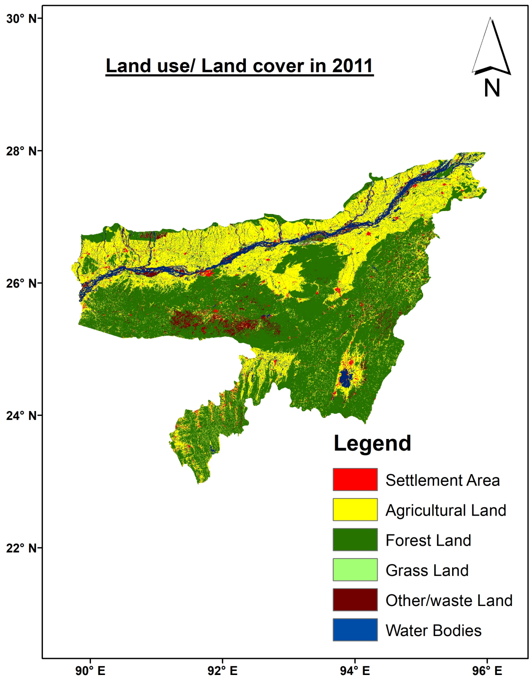

Figure A6: Landuse/Land cover in 2011

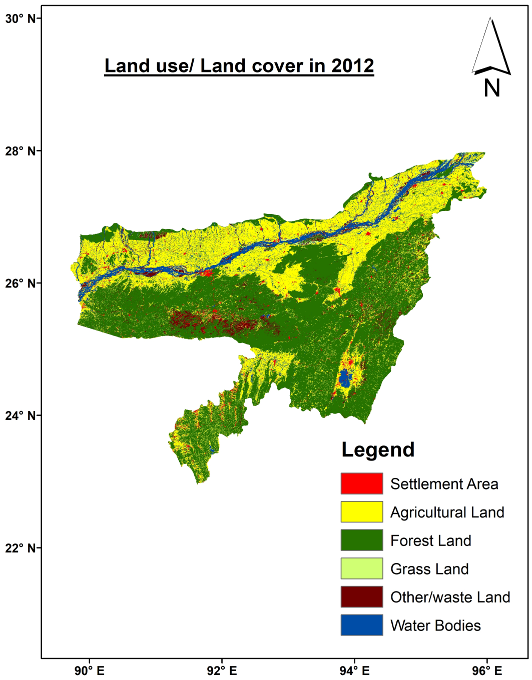

Figure A7: Landuse/Land cover in 2012

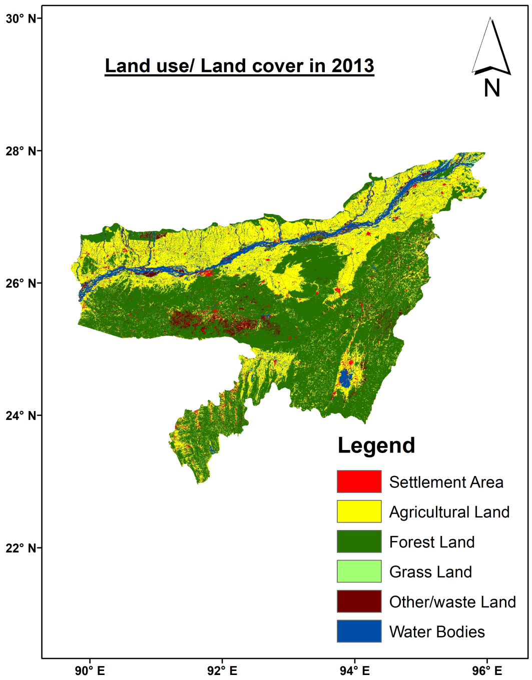

Figure A8: Landuse/Land cover in 2013

Papers and conferences

Journal

- Hinge, G., Surampalli, R. Y., and Goyal, M. K. (2018) "Prediction of soil organic carbon stock using digital mapping approach in humid India" *Environmental Earth Sciences*,77(5), 172.
- Hinge, G., Surampalli, R. Y., and Goyal, M. K. (2018) " Regional carbon fluxes from land-use conversion and land-use management in Northeast India" *Journal of Hazardous, Toxic, and Radioactive Waste*, 22(4), 04018016
- Hinge, G., Surampalli, R. Y., and Goyal, M. K. (2019) "Effects of Landuse and Soil Management on Soil Quality in India's Northeastern Himalayas" *Journal of Environmental Engineering*, 145(4), 04019007
- Hinge, G.,Sarma, A.K., Surampalli, R. Y., and Goyal, M. K. "Altitudinal pattern and its control on plants and soil carbon concentration" (To be submitted)
- Hinge, G.,Goyal, M. K, Surampalli, R. Y., and Sarma, A.K..."Carbon Stock and Associated Soil Resilience under Varying Climate Conditions" (To be submitted)

Book chapter

- Gilbert Hinge, Rao Y Surampalli, and Manish Kumar Goyal (2019) "*Sustainability of carbon storage and sequestration*", Chapter 22 in Sustainability: Fundamentals and Applications. Edited by: R. Y. Surampalli, T. C. Zhang, M. K. Goyal, S. K. Brar and R. D. Tyagi. [Accepted]

Conferences

- Gilbert Hinge, Pulendra Dutta and Arup Kumar Sarma (2019) "Soil organic carbon and soil aggregation enhancement from vermicompost management enriched with biofertilizers" Asia Oceania Geosciences Society conference, Singapore. 28 July-2 August 2019.