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# Effect of Elevation and Above Ground Biomass (AGB) on Soil Organic Carbon (SOC): A Remote Sensing Based Approach in Chitwan District, Nepal

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**Abstract**— Now a days the possibility of enhanced carbon storage in soils is of more interest compared to vegetation as it contains more carbon. For this reason, the revised Kyoto protocol includes two new clauses relevant to soil organic carbon sequestration. So, for the countries that have signed the Kyoto protocol, estimation of SOC sequestration is a required strategy. Reliable quantification of carbon held in soil is essential to formulate any kinds of monitoring program. This SOC is dominated by a lot of variables like environmental and soil internal factors as well. This study aims therefore to study the effect of two remotely sensed measured variables on SOC in the subtropical forest of Chitwan, Nepal.

Two variables, above ground biomass (AGB) and elevation and other two soil parameters bulk density and soil pH were analysed in context of soil organic carbon. Although soil bulk density and pH cannot be measured through remote sensing technology, they were used to test the relationship. Soil organic carbon was analysed through Walkley-Black and Loss on Ignition (LOI) methods. Canopy Height Model (CHM) was developed from LiDAR data by subtracting the Digital Terrain Model (DTM) from the Digital Surface Model (DSM) to estimate the height of the trees. This CHM image was segmented based on an Object Based Image Analysis (OBIA) technique using e Cognition software. Segmented CPA further analysed to develop a model for DBH prediction. With the information of DBH, tree height and wood specific gravity, AGB was calculated. Elevation height was extracted from LiDAR derived DEM.

Results show that there is a positive relationship ($r = 0.79$) between soil organic carbon and above ground biomass ($p<0.001$). Elevation and soil organic carbon is also positively correlated ($r=0.74$).

**Index Terms**— Soil Organic Carbon(SOC), Bulk Density (BD), Soil pH, Litter Quality (LQ), Loss on Ignition(LOI) , Walkley – Black(WB) method, Stepwise regression, Biomass, Crown Projection Area(CPA), Diameter at Breast Height(DBH), Species Diversity, Allometric equation.



## 1 Introduction

THE atmospheric concentrations of CO2 and other greenhouse gases (GHGs) has increased drastically since the industrial revolution[1]. According to the records of [2], the concentration of atmospheric CO2 has increased from 280 ppmv in 1750 to 367 ppmv in 1999 and the current increasing rate is 1.5 ppmv/year or 3.3 Pg C/year [2]. The main greenhouse gases (CH4, N2O and CO) and their cumulative pressure in the atmosphere has led to an increase in the average global surface temperature of 0.6 °C since the late 19th century, with a current warming rate of 0.17°C / decade [2]. The global carbon budget for the decade of 1990-2000 included an emission of 6.3±0.4 Pg C from fossil fuel combustion and cement production and an emission of 1.6±0.8 Pg C from land use change [3]. The mentioned data indicate that land use, soil management and terrestrial ecosystems play an important role in the global C budget. Due to land use, land use change, forestry and other forest activities like biomass burning, fertilization and wetlands restoration, the emission of CH4 and N2O is increasing. In a same time, terrestrial ecosystem, in which C - is stored in live biomass, plant litter, organic matter and soil play an important role in the global carbon cycle. There are five main global carbon pools: the oceanic, geologic, pedologic (soil), biotic and the atmospheric pool. These five C pools are connected with each other and C exchanged from one pool to other through photosynthesis, respiration, decomposition and combustion. Proper monitoring and accurate estimation of these pools help to initiate the mitigation steps of climate change (CC).

About 2,500 Pg of Carbon (C) is stored in soil, compared to 760 Pg in the atmosphere [4]. Globally forest vegetation and soils removed carbon from the atmosphere at a rate of 4.7±1.2 Gt (Giga tones) per year in 2008, compared to carbon emissions from fossil fuels and deforestation of 8.7±0.5 Gt per year and 1.2±0.7 Gt per year respectively [5]. Therefore, biomass C and soil C are considered two important components of carbon storage in forest ecosystem. In forest, biomass and soils contain about 1240 Pg of C [6]. Compare to biotic pool soil pool stores more carbon. Soil carbon pool is the combination of soil organic carbon (SOC) and soil inorganic carbon (SIC). Due to the large areas involved at regional or global scale, forest soils play an important role in the global C cycle [7].

The SOC pool of forest soils acts as a sink for plant nutrients (e.g., N, P, S, Zn, Mo) and charge density and responsible for ion exchange. SOC is the promoter of soil aggregation that improves soil tilth. Soil organic carbon increase available water capacity in plant due to absorbent of water at low moisture potential. It buffers the emissions of GHGs from soil to the atmos-

phere [8]. It causes of high water infiltration capacity and low losses due to surface runoff. Soil organic carbon is the source of strength for soil aggregates leading to reduction in susceptibility to erosion. It substrates energy for soil biota leading to increase in soil biodiversity. SOC is responsible of high nutrient and water use efficiency because of reduction in losses by drainage, evaporation and volatilization. SOC buffers against sudden fluctuation in soil reaction (Ph) due to application of agricultural chemicals. It is a moderator of soil temperature through its effect on soil color and albedo.

With advances in climate change mitigation through Reducing Emissions from Deforestation and forest Degradation (REDD), much emphasis has been put on above ground carbon but less attention given to below ground carbon. But if SOC changes with forest loss, and varies with land use, such carbon may play a significant role in local, national and global carbon budgets. We therefore need more data on SOC stocks. Due to much focus on biotic pool and biomass estimation, soil organic pool (SOC) is always ignored or very few works have been done on it in context of remote sensing. Instead of direct destructive method (cutting and weighing) remote sensing technology are using to improve the monitoring and accurate estimation of tree biomass.

**Factors affecting the soil organic carbon pool:**

The size of the soil organic matter pool depends upon plant growth, litter formation rate, the extent and rate of mineralization of the plant residues entering the soil. This complex process is controlled by several factors including soil type, temperature, and precipitation rate, biochemical composition of the plant residue and the nature and abundance of decomposing organisms. The environmental variables such as: altitude, slope and landscape position can impact on the soil's C stock. This is because of their influence on the soil temperature, soil water and pore space retention [9]. Among those factors, some are very much correlated and mentioned in the steps of SOC formation process are discussed below:

**Above ground biomass:**

How much litter will be deposited at or under the soil surface depends on the above ground biomass and its type. Plant types and amount of biomass significantly affected the distribution of SOC [10]. According to their study, the percentage of SOC in the top 20 cm averaged 33%, 42%, and 50% for shrub lands, grasslands, and forests, respectively. They also concluded that globally the relative distribution of SOC with depth had a slightly stronger association with vegetation than with climate. [10] suggested that shot/root allocations combined with vertical root distributions, affect the distribution of SOC with depth.

Not only the shoot/root ratio, the amount of soil organic carbon also influenced by the litter that deposited from the above biomass and root decomposition. Different chemicals and their amount in leaf, foliage has a relation with litter and can be used as a substitute for litter quality. However, there is no universal litter quality index because litter decomposition depends on qualities which differ among species and plant parts. The rate of litter decomposition is associated with the lignin and nitrogen content. So the decomposition of litter turning into soil organic carbon (SOC) is determined by the degradation rate of lignin. During the oxidation process lignin decomposes slowly, much slower than cellulose.

**Effect of Elevation and topography on SOC:**

Among all the environmental variables those that play the most vital role are slope and elevation. The strong effect of slope and aspect on SOC stock was found in research done of a subalpine forest in the Olympic Mountains of Washington state [11]. They found that soil organic carbon increases with elevation distance up to 1600m. [12] found that soil carbon increased with elevation and in their study, they found an almost four fold increase in soil carbon, from 2.1 to 8.0% (mass based) between 600 to 1600m. In high-altitude ecosystems soils play a vital role in the global terrestrial carbon cycle due to their large carbon stock [13]. It happens due to a number of unique factors, e.g. permafrost, cold temperature and water-logging [14].

Change of elevation distance has a relation with temperature and precipitation. The higher the elevation height, temperature is going to be colder. In same way in high elevation range, rainfall and precipitation are more active to facilitate the anaerobic condition into the soil system due to it's waterlogging, frosting and others related climatic parameters which already discussed in previous paragraph.

As soils sink more carbon than atmosphere and vegetation combined, and can hold it longer, research interest are increasingly looking to soil carbon as an opportunity to mitigate climate change. For regular monitoring, correct algorithms or feasible strategies are essential to estimate soil organic carbon. Remote sensing based technologies for soil organic carbon monitoring still are in a process of establishment. So this study is proposed to know the effect of two variables that can be measured through remote sensing technology on soil organic carbon. Those variables are Above Ground Biomass (AGB) and elevation.

The main aims of this research are to assess the effect of elevation and aboveground biomass on Soil Organic Carbon (SOC) and how can we estimate those two variables through a remote sensing technology to make the estimation process easy. Specific objectives of this study are:

1. To evaluate the effect of elevation on SOC in Community Forest (CF) of Nepal.
2. To evaluate the effect of above ground biomass (AGB) in Community Forest (CF) of Nepal.

## 2 Materils and Methods

### 2.1. Area of Study

The study be found in Chitwan district of Nepal (figure-1). The area is situated between 27°30'51"N - 27°52'01 N latitude and 83°55'27"E - 84°48'43"E longitude and surrounded by the Makwanpur district in the east and the Nawalparasi in the west. The neighboring districts in the northern part are Dhading, Gorkha and Tanahu while Parsa district and India are located on its southern borders. Chitwan is situated 68 kilometers south east (133°) of the approximate center of Nepal and

82 kilometers west (260°) of the capital Kathmandu. The elevation height varies from 200 m -1100m above sea level. Out of 2218 km² of the total district area, Kayerkhola Watershed, the study area is covered by 660. ha of forest including 3 community forest [15]. The respective areas occupied by three community forest are as follows: Devidhunga 253 ha, Nibuwatar 329 ha and Janpragati 78 ha.

For this research and field work, Worldview-2 high resolution satellite imagery (multispectral 2m and panchromatic 0.5m) obtained on 25th October 2010 and small footprint airborne Lidar data (0.5-2 points/m2) obtained in March 2011 were used. Data were already pre-processed. Topographic map was also used in the field during data collection.

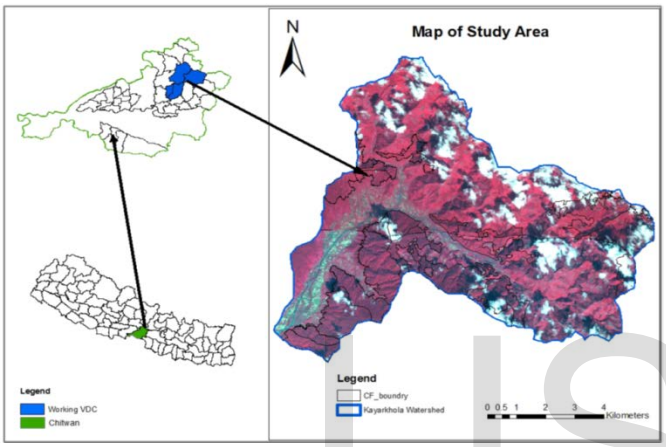


Fig1 Study area of the research.

**Extraction of Elevation data**

Digital Elevation Model (DEM) of the study area was used to extract the elevation data of the study area. The whole elvation range was divided into five groups to collect the data and to know the effect of elevation according to the spatial distance. For example,

i) 200-400 meter
ii) 401-600 meter
iii) 601-800 meter
iv) 801-1000 meter
v) More than 1000 meter

**2.2. Methodology**

The whole methodology of this work are divided into seven segments to describe it in a logical order, such as-

i) Part-A: Tree and soil parameters related data collection from the study area.

ii) Part-B: Soil sample analysis in the laboratory to extract soil organic carbon data

iii) Part-C: Canopy Height Model (CHM) preparation from LiDAR data to extract Canopy Projection Area (CPA) and height information and DEM for elevation information.

iv) Part-D: Regression model development to estimate AGB for study area.

v) Part-E: Relationship between SOC and elevation and above ground biomass.

**Soil sample collection and analysis**: Most commonly used methods of SOC determination are: a) Walkley –Black Method and b) Loss On Ignition Method [16]. In this study, both methods were used to measure the carbon content from forest soil.

**Canopy Height Model for Biomass estimation**: To find the exact location of a tree, a canopy height model (CHM) was extracted from LiDAR data. By subtracting the Digital Surface Model (DSM) from Digital Terrain Model (DTM), a CHM was derived to calculate the tree height. [17] used the same method to develop a CHM. First two steps i.e DTM and DSM were extracted using LasTools software but the third step i.e CHM preparation and height calculation was done in ArcGIS by raster calculator. As an output, a C0048M with 0.5 m spatial resolution was prepared which contains pixel values of the height of trees.

**Sampling design**: A stratified random sampling design was adopted. Stratification is the statistical sampling approach of dividing members of the population into homogeneous subgroups or strata. After dividing into these strata, simple random sampling was applied within each statum.to improve the representativeness of the total sample as well as to reduce the sampling error. The whole study area was divided into 5 elevation strata, each stratum covers a 200 m interval. The actual number of sampling points per elevation stratum was determined by using the following formula adopted from the Community Forest Inventory Guideline of Nepal (DoF, 2010)

**Determination of sampling plot number**

Area of sampling (m² )=sampling intensity(%)×Total area of stratum(m²)

No of plot(n)=(Area of sampling(m²))/(Area of one sample plot(m²))

**Measuring tree parameters**

The XY coordinate of the centre of each plot (500m² plot) was located using an iPAQ. Within each main plot, only trees with a DBH of 10 cm or greater were measured because trees with less than 10cm have a small contribution to the total biomass of a forest [16]. The following tree parameters: DBH, tree height, crown cover and crown diameter were measured in the sample plot. DBH and height were measured to estimate the biomass of individual tree through allometric equation. Crown diameter was measured to calculate the CPA of tree. For Shannon Diversity Index analysis, all the species within the plot were identified and noted on the sheet. Slope correction has been done in the areas more than 5 ° slope during the measurement of plot radius and crown diameter.

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# 3 Result

**3.1. Descriptive statistics related to soil parameter**:

Three parameters related to soil named bulk density, soil pH., soil organic carbon were measured for each sample. Average value of these soil properties are presented below (Table 1) according to the elevation range. To get an overall view of the status of soil and to collect variables data for soil organic carbon (SOC), soil pH, and soil bulk density results were prepared. The ranges of SOC in high elevation (600– 1000) is higher to other ranges. According to Table 1, results in standard deviation indicating the values are close to mean and sows a low variability from all parameters.

Table 1: Ranges of different soil parameter values at different elevation ranges.

| Elevation Distance (m) | Bulk Density (gm./cm$^3$) | Soil pH | Soil Organic Carbon (WB) | Soil Organic Carbon (LOI) |
|---|---|---|---|---|
| 200-400 | 1.17-1.69 | 4.70-5.37 | 0.73 - 3.10 | 1.35 to 4.09 |
| 401-600 | 1.11-1.66 | 4.42-5.71 | 0.62 - 3.15 | 1.2 - 4.75 |
| 601-800 | 1.14-1.65 | 4.34 - 5.72 | 1.78 - 3.14 | 2.15 -3.95 |
| 801-1000 | 1.19-1.24 | 3.91-5.58 | 2.64 - 3.98 | 3.51 - 4.16 |
| Mean Value | 1.37 | 4.9 | 2.29 | 3.01 |
| SD | 0.15 | 0.38 | 0.71 | 0.72 |

**3.2. Estimation of Elevation sampling points:**


Fig 2.a. Sapling points


Fig 2.b. Elevation rang distribution of study area.

Randomly selected 61 sample points from different elevation were used to know the effect of elevation on SOC. Soil sample location was also on the same points of elevation data. After analysing the soil sample of the same location a regression line will be developed to make a relationship between soil organic carbon and elevation data.

**3.3. Estimation of above ground biomass data**

Above ground biomass data was also calculated from the same sample location of elevation and soil carbon. Detailed process of above ground data estimation is discussed below:

Development of regression model for DBH prediction:

Four different types of models (linear, logarithmic, polynomial and power) were performed to compare the relationship between Crown Projection Area (CPA) and the diameter at breast height (DBH). All models were developed to extract the regression and RMSE value. Based on the lowest RMSE and highest $R^2$ value, Only one model was selected to derive tree biomass from the LiDAR CHM segmented image for the entire study area.

Fig.3.a Manual delineation of tree canopy.


Fig. 18. Segmented CPA and manual delineated CPA.

Table 2. Represents different kinds of DBH predicted model.

| Data sources | Name of the model | Regression model | R2 | r | RMSE | RMSE % |
|---|---|---|---|---|---|---|
| Field observed data | Linear | 0.5744*(CPA)+20.81 | 0.71 | 0.84 | 8.68 | 16.23 |
| | Logarithmic | 26.87*ln(CPA)-52.78 | 0.66 | 0.81 | 9.33 | 17.21 |
| | Polynomial | $0.0018*(CPA)^2+0.3746*(CPA)+25.48$ | 0.71 | 0.84 | 8.96 | 17.59 |
| | Power | $6.19.1*(CPA)^{0.5347}$ | 0.68 | 0.82 | **8.64** | **16.18** |
| LiDAR CHM segmented image | Linear | 0.39*(CPA)+28.719 | 0.68 | 0.82 | 9.64 | 18.02 |
| | Logarithmic | 22.45*ln(CPA)-36.57 | 0.64 | 0.80 | 11.42 | 21.45 |
| | Polynomial | -0.0004(CPA)2+0.4548*(CPA)+26.76 | 0.68 | 0.82 | 10.42 | 19.48 |
| | Power | $9.2928*(CPA)^{0.4257}$ | 0.66 | 0.81/ | **9.17** | **17.14** |



### 3.4. Model Validation

From table 2, it is clear that power model gives the lowest RMSE in both cases for field observation data set and as well as for LiDAR data. So power model was selected as a best model to predict the DBH by using CPA parameter. To test the accuracy of the model two different linear regressions were performed. At first field measured CPA was plotted with segmented CPA. Here validation data set was used to test the relationship. The correlation coefficient indicates that they are strongly correlated. Same validated dataset was used to know the strength of the power model. Here field CPA was plotted against estimated CPA, predicted DBH was plotted against the independent field observed DBH data and predicted biomass was plotted against observed biomass. The linear regression line shows the $R^2$ is 0.68 for CPA, 0.63 for DBH and 0.72 for biomass (Fig 4, a.bc).

### 3.5. Above Ground Biomass (AGB) estimation and map preparation

To estimate above ground biomass for the study area allometric equation ( AGB = 0.0509 *$\rho$ *D2H) was used. Here sole input DBH was replaced by the CPA developed from power regressions model. So the final equation was

$$AGB = 0.0509 \times \rho \times \left\{9.2928 \times \left(CPA\right)^{0.4257}\right\}^2 \times H$$

a)


b)


c)

Fig 4(a,b,c): Relation between estimated CPA, DBH and Biomass with observed CPA, DBH and biomass.

Where
AGB = above ground biomass (kg)
$\rho$ = wood specific gravity (= 0.88 gm/cm3) and
CPA = Crown Projection Area (CPA) from LiDAR CHM segmented image
H = tree height (m).

The figure 5 shows the estimated amount of above ground biomass for the whole study area. Total 230 Gg was estimated in the whole study area. The mean value of biomass is 592.33 kg/tree. LiDAR derived biomass comes from two types of input with two types of uncertainity. Here DBH was predicted from segmented CPA, one uncertainity and another uncertainity is LiDAR derived tree height. So it is necessary to check to what extent these two uncertainities propagate into the final result. To validate this result a linear regression line was fitted with field observed tree biomass against the biomass estimated from the segmented image from the same reference tree.


Fig.5. Above ground biomass of the study area.


Fig.6. Field observed and estimated biomass (kg/tree).

**3.6. Relationship of soil organic carbon with elevation and above ground biomass**:

Correlation matrix was also prepared for all variables. From the correlation matrix, it was found that above ground biomass and elevation are highly correlated. Correlation coefficient value (r=0.84), indicates there is a positive correlation. It means that higher elevation has higher biomass.


Fig 6.a Relation between soil organic carbon and elevation


Fig 6.b. Relation between soil organic carbon and above ground biomass

Table3 Summary of correlation matrix showing the correlation value.

| | SOC | Elevation | AGB | Variance Influence factor (VIF) | | |
|---|---|---|---|---|---|---|
| SOC | 1.00 | 0.74 | 0.79 | SOC | Elevation | AGB |
| Elevation | 0.74 | 1.00 | 0.84 | 3.19 | 4.11 | 5.39 |
| AGB | 0.79 | 0.84 | 1.00 | | | |

## 4 Discussion

Based on lowest RMSE power model was selected for DBH prediction. In same study area, [18] tested power and exponential model to calculate the AGB separately. He concluded that exponential model was unable to predict the DBH for those trees with a CPA more than 250 $m^2$. During field work, it was not found any tree with a CPA more than 250 m2. Current sampling plot were completely different from [18]'s plot. But it can't be denied that trees with a large CPA were there.

Results may be compared with the finding of [19]. He found that for broadleaved forest power model fits better for DBH measurement compares to exponential model. He classified six broadleaf species. For all species power model give better correlation coefficient (r > 0.86 for all species) compare to exponential model.

From the result of biomass map it was found that the mean value of biomass was 592.33 kg/tree which one is closer to mean biomass of observed value in the field. From field observed data, biomass of major species was estimated and it varied from 374.98 kg/tree (*Lagerstromia parviflora)* to 1263 kg/tree (*Semicarpus anacardium*). The segmented image was not classified into species level. During the implementation of allometric equation, wood specific gravity was counted as common for all species (0.88 gm/cm3). This is one of the limitations of this estimation. The other uncertainty occurred in this map due to the segmentation accuracy. The maximum range of biomass observed in field was 11,198 kg/tree (based on height and DBH). But in case of segmented biomass map, the highest range was 30237 kg/ tree (based on LiDAR height and predicted DBH). So this uncertainty comes from three sources one from the error of predicted DBH, another one from the LiDAR height accuracy and last one big crown or cluster of tree crowns which appeared as a single tree crown in segmentation. Therefore this result was validated with the field observed biomass. The correlation coefficient value (r=0.84) indicates that there is a strong positive correlation between field observed biomass and LiDAR CHM segmented biomass. So the biomass extracted from LiDAR data is reliable to make relationship with soil organic carbon.

From the result of relationship between soil organic carbon and elevation, it was found a positive correlation between soil organic matter and elevation. Higher elevation means cold, low temperature and more waterlogged condition that helped to retain more organic carbon in the soil. This result is supported by [11] who found that soil organic carbon increases with elevation distance up to 1600m.

The relationship between soil organic carbon and above ground biomass was showing a positive trend and correlation coefficient r=0.79 indicates that they have a very strong correlation. This positive correlation is due to higher biomass means higher litter deposition, more organic matter and consecutively more soil organic carbon. This result is supported by the findings of [10] who found a positive correlation between soil organic carbon and litter/root-shoot ratio of above ground plants.

## 5 Conclusion

The main aims of this research were to assess the effect of elevation and aboveground biomass on Soil Organic Carbon (SOC) by using airborne LiDAR measured variables. In his regards, conclusions are based on the research questions as follows: (i) Based on the correlation matrix, it was found that elevation and SOC are both positively correlated. It was expected that this strong correlation (r =0.74) was the reflection of the fact of that there was a strong correlation between above ground biomass and elevation. (ii) From this study, it was proved that there is a strong positive correlation between soil organic carbon (SOC) and above ground biomass (at 95% confidence interval, p value < 0.001).

So soil organic carbon is affected by using variables, above ground biomass and elevation and both of them can be measured by LiDAR data.

Estimation of soil organic carbon (SOC) based on remote sensing variables is a new and emerging field of work. As the sufficient amount of remote sensing data was available for this study area, the work was conducted based on the available remote sensing data. But litter quality is not a direct ground sampling representative data. Plant litter sample was not collected during field work to make a relationship with the SOC and litter quality. Only litter index was prepared based on species class to make dummy variables for stepwise regression. So for further improvement of SOC estimation through RS data the following works may be recommended, (i) Species diversity should be a criterion in sampling design to judge the correlation between soil organic carbon and species diversity. This current study ignored this criterion. For further investigation and study area selection, species composition and diversity should be analysed before selecting the sampling design., (ii)The ground samples represent a linear positive relationship between biomass and elevation. Further sampling is recommended at a location with low biomass and a higher elevation or vice versa.

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