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Proxies for soil organic carbon derived from remote sensing

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ABSTRACT

The possibility of carbon storage in soils is of interest because compared to vegetation it contains more carbon. Estimation of soil carbon through remote sensing based techniques can be a cost effective approach, but is limited by available methods. This study aims to develop a model based on remotely sensed variables (elevation, forest type and above ground biomass) to estimate soil carbon stocks. Field observations on soil organic carbon, species composition, and above ground biomass were recorded in the subtropical forest of Chitwan, Nepal. These variables were also estimated using LiDAR data and a WorldView 2 image. Above ground biomass was estimated from the LiDAR image using a novel approach where the image was segmented to identify individual trees, and for these trees estimates of DBH and Height were made. Based on AIC (Akaike Information Criterion) a regression model with above ground biomass derived from LiDAR data, and forest type derived from WorldView 2 imagery was selected to estimate soil organic carbon (SOC) stocks. The selected model had a coefficient of determination (R^2) of 0.69. This shows the scope of estimating SOC with remote sensing derived variables in sub-tropical forests.

1. Introduction

Soil organic carbon (SOC) stocks build up under forests as a result of inputs from primary production and possible exogenous organic matter additions (e.g., composts and manure). Soil organic carbon pools may play a significant role in local, national and global carbon budgets (Watson et al., 2000) because they can become much larger in total stock than the above ground biomass component in forests (Eswaran et al., 1993; Lal, 2004). However, due to a primary focus on the aboveground biotic (AGB) carbon pool, the SOC pool has been to large extent ignored and only few studies, e.g. (Dixon et al., 1994; Eswaran et al., 1993; Jobbágy and Jackson, 2000) have been performed to produce estimates of it.

One inherent reason why SOC pools in forests have been largely ignored is the difficulty to make use of remote sensing to monitor them. Forest cover obscures a direct view of the soil and subsequent deduction on SOC stocks. Direct remote sensing based quantification of SOC pools still require laboratory conditions and large remaining errors are reported (Bartholomeus et al., 2008). A very few studies (Uno et al., 2005; Bartholomeus et al., 2011; Vaudour et al., 2016) have been reported for the prediction of SOC from direct remote sensing platform. However, more recently, Nocita et al. (2012) and Vaudour et al. (2016) concluded that SOC quantification from reflectance suffered from partially covered soil surface roughness, rock fragment coverage, vegetation cover and moisture content. Still, remote sensing is often preferred over field based methods because it offers the opportunity for consistent and repeatable measurements over large extents and is often less expensive when applied over large areas. Heterogeneity in SOC stocks can be associated with variability in topography, stoniness, parent material, soil depth and environmental condition (Usuga et al., 2010). Some of these correlated conditions are much better directly or indirectly estimated using remote sensing. When Wasige et al. (2014) used Landsat and ASTER DEM data to analyze land use change, and its impact on SOC content, they found higher SOC stocks under forest cover compared to agricultural cover types. Therefore, perhaps SOC pools can be estimated based on remote sensing data of correlated conditions. This study investigated to what extent remote sensing based observations of associated variables can be used to assess variation in SOC pools in areas that are under forest cover. We start with a review of relevant parameters that can be measured with remote sensing, which have a logical link with SOC pools. Subsequently we will describe the study design and the results and how these parameters might be used in future studies to assess SOC pools in forest soils. The study was performed in

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sub-tropical forested region in Chitwan province, Nepal. Here, Sal trees are the dominant vegetation cover, although there are areas with mixed forests as well. We realize that a specific region or study area and specific forest type does not immediately yield globally generalizable results, but it does give an indication of the accuracy with which SOC stocks can be derived from indirect remote sensing based estimation.

1.1. Factors affecting SOC

The size of the SOC pool in forests depends mainly upon the litter formation rate, and the extent and rate of mineralization of the plant residues entering the soil (Bot and Benites, 2005). Next to these two fundamental processes, run-off, run-on and leaching resulting from rainfall events can be a reason for dynamics in SOC pools. However, in forests these processes play a minor role, because forest has a stabilizing effect on erosion processes (Bot and Benites, 2005). The litter formation and mineralisation processes are controlled by several factors including soil type, temperature, precipitation, biochemical composition of the plant residue and the nature and abundance of decomposing organisms. These in turn can be influenced by topographical variables such as altitude, slope and landscape position that influence soil temperature and soil water content (Gulledge and Schimel, 2000). We will discuss the main factors below.

1.1.1. Clay content and mineralogy

Soil texture and mineralogy have been identified as relevant to SOC retention (Christensen, 1992). Jobbágy and Jackson (2000) found that SOC is greatly influenced by soil texture (sand and clay content) after 20 cm depth. Similarly, Badgery et al. (2013) found that the influence of texture and mineralogy are most pronounced at 20–30 cm depth. Clay content is an important parameter that affects the way organic matter decomposes. In Rothamsted Carbon Model (Roth-C), this clay content is counted as an important parameter for labile carbon turnover estimation. There is a strong relationship between fine fraction (silt and clay particles <20 μm) and the amount of SOC stored in this fraction in uncultivated grassland soils (Hassink, 1997). In a very recent study, Wiesmeier et al. (2015) also found a strong linear correlation between the proportion of fine fraction and its SOC content. However, both of the studies were related with degraded dry land soil.

1.1.2. Soil aggregation

Soil aggregate dynamics also strongly influence C seque**s**tration and cycling (Tisdall and Oades, 1982; Jastrow, 1996; Six et al., 1988). Tisdall and Oades (1982) presented a hierarchical model, which suggested that three different classes of organic matter (persistent, transient, and temporary) are associated with three different physical soil fractions, that is >250-μm macroaggregates and <53-μm silt-and-clay, respectively. The importance of microaggregates in the protection and stabilization of C is recognized by several recent findings (Jastrow, 1996; Six et al., 2000; Denef et al., 2004). In addition, Denef et al. (2004) showed that microaggregates within-macroaggregates could explain almost the entire difference in SOC between no-tillage and conventional tillage systems.

1.1.3. Soil pH

Soil pH has a significant effect on soil organic matter preservation and decomposition, although its precise influence still needs to be fully determined. There are a lot of conflicting views concerning the relationship between soil pH and soil organic matter. Spain (1990) found a negative correlation between soil organic matter and soil pH in tropical rainforest soils. On the other hand, Hardon (1936) observed that in acidic soils organic carbon contents increased. The most important chemical reaction in SOC systems are humification and mineralization. These processes are responsible for changing the chemical composition of soil organic matter and are of great importance to the terrestrial carbon cycle. Soil pH mainly affect these two chemical reactions specially lignin decomposition. Guggenberger et al. (1995) observed a significant lignin contribution in strongly acidic soils with a pH < 5.0, whereas moderate acidic soils with pH > 5.0 showed little evidence of lignin. Motavalli et al. (1995) also suggested that acidic soil reduces the decomposition rates of freshly added organic materials.

1.1.4. Above ground biomass

How much litter will be deposited at or under the soil surface depends on the above ground biomass and the type of forest (Jobbágy and Jackson, 2000). Esteban and Robert (2000) found a direct relation between plant type, amount of biomass and the distribution of SOC. They also suggested that shoot/root allocations combined with vertical root distributions affect the distribution of SOC with depth.

1.1.5. Species and litter composition

The SOC pool is also influenced by the composition of litter that is deposited by above ground biomass and from root detachment. The different chemical and physical composition of litter influences its decomposability and therefore the rate at which SOC stocks decline through decomposition. Higher concentrations of complex secondary compounds, such as lignins and tannins can slow down the decomposition rate while litter with high levels of nitrogen generally decompose faster (Kasel et al., 2011). Litter composition is influenced by the growing conditions of plants. In nitrogen limited systems, plants tend to have lower nitrogen levels while older plants tend to have higher tannin and lignin levels (Lerouge et al., 1998). Roots decompose faster than leaves at more infertile sites, in part because of lower lignin-to-nitrogen ratios in roots than in leaf litter. Overall, species type itself is having an overruling effect on litter composition and thus decomposition rate (Saha et al., 2009).

1.1.6. Temperature

Enzymatic activity during decomposition normally increases with temperature, but rapidly falls as the temperature rises above an optimum value. Deqiang et al. (2008) showed that increasing temperature from 15 °C to 18 °C significantly increases CO_2 emissions from the litter. Generally trees growing under warmer and wetter climates (and thus with higher actual evapotranspiration) tend to shed foliar litter richer in N than those growing under colder and drier climates. When more N accumulates, decomposition rates also increase. Higher decomposition rates mean lower SOC stocks.

1.1.7. Precipitation

Rainfall affects various soil biological activities because of its influence on soil moisture and temperature. Low moisture levels reduce metabolic activity (Grizelle and Timothy, 2001). How this affects decomposition rates varies per compound (Grizelle and Timothy, 2001), so the ultimate effect of rainfall on total SOC stock is difficult to predict.

1.1.8. Elevation and topography

Elevation and topography have a relation with temperature and precipitation (Lal, 2001). Generally, at higher elevations temperatures are lower and, depending on the orientation of a slope, rainfall is generally higher (the orographic effect). Therefore elevation and topography can have indirect correlation with SOC pools. For example, Prichard et al. (2000) observed in a subalpine forest in the Olympic Mountains of Washington state that the SOC pool increased with elevation up to 1600 m. Similarly, Lal (2001) found that the SOC pool increased with elevation and, in his study he