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Digital soil mapping of soil organic carbon stocks under different land use and land cover types in montane ecosystems, Eastern Himalayas

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ABSTRACT

Quantification of soil organic carbon (SOC) stocks is quite useful for accurate monitoring of C sequestration. However, there are still substantial gaps in our knowledge of SOC stocks in many parts of the world, including the Himalayas. We investigated the total SOC stocks and its spatial distribution under different land use and land cover (LULC) types in montane ecosystems of Bhutan. 186 Soil profiles were described and sampled by genetic horizons at sites located using conditioned Latin hypercube sampling. SOC concentrations at the standard depths designated for the *GlobalSoilMap.Net* were estimated with an equal-area spline profile function. SOC concentrations at these depth intervals were digitally mapped to a fine resolution matrix of 90 m grid using regression kriging. We found significant influence of LULC categories on SOC concentration, SOC density, SOC stocks and their spatial distributions, although this influence decreased with increasing soil depth. The estimated mean SOC density in the top 1 m were highest in fir forest soils (41.4 kg m^{-2}) and lowest in paddy land (12.0 kg m^{-2}). Allowing for LULC relative areas, mixed conifer forest had the highest SOC stocks in the upper meter (12.4 Mt) with orchards the lowest (0.1 Mt). The total SOC stocks for the whole study area for the 0–5, 5–15, 15–30, 30–60 and 60–100 cm depths were 2.6, 5.0, 6.5, 7.5 and 5.4 Mt, respectively. The overall SOC stock of the study area for the upper meter was approximately 27.1 Mt. The combined forests accounted for more than 77.5% of the total SOC stocks of the study area. This and the relative SOC densities indicate that the conversion of even a fraction of forests to other LULC types could lead to substantial loss of SOC stocks. This loss of SOC stock is even greater when the decrease in aboveground biomass is also taken into consideration. However, appropriate management of the agricultural lands could increase their sequestration of atmospheric CO_2.

1. Introduction

Soil organic carbon (SOC) is the largest terrestrial pool of sequestered carbon (C) (Batjes, 1996; Chhabra et al., 2003) and therefore plays a pivotal role in global C dynamics. Previous estimates, based on vegetation units (Post et al., 1982) and soil taxonomic units (Batjes, 1996), indicate that the soil stores about 1500–1600 PgC in the upper meter. Jobbágy and Jackson (2000) estimated about 2344 PgC for the upper 3 m (with 1502, 491 and 351 PgC for the first, second and third meters, respectively). SOC is not just an inert C store, as it also influences the physical, chemical and biological properties of the soil (Dexter et al., 2008), which have significant impact on sustainability of agriculture. SOC is therefore an indicator of both soil quality and environment stability (Saha et al., 2011). As sequestration of atmospheric CO_2 in soils is an option to reduce global warming (IPCC, 2007), baseline data and information on SOC storage are essential for characterizing C dynamics and C trading (Stockmann et al., 2013). Consequently, modeling and quantification of the spatial distribution of SOC stocks is necessary to find the SOC sink capacity of soils (Mishra et al., 2009) for enhancing C sequestration.

The quantification of SOC stocks relies on understanding the spatial variability of SOC stocks in a landscape, which in turn requires identification of its controlling factors including, land use and land cover (LULC) types (Sitaula et al., 2004; Smith, 2008; Saha et al., 2011). LULC types affect SOC storage by determining the amount and quality of soil organic matter inputs, and by influencing their decomposition and stabilization (Six et al., 1999, 2002).

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Many studies have reported large SOC stocks under forest compared to grassland and agricultural land (Guggenberger et al., 1994; Cai, 1996; Lal, 2004b; Abbasi et al., 2007; Yang et al., 2009; Saha et al., 2011). However, in most previous studies only generalized LULC types were considered (Shrestha et al., 2004; John et al., 2005; Tan et al., 2007), which precluded the deciphering of more detailed and complex interactions between the SOC stocks and LULC types.

While the spatial variability of SOC concentration, bulk density and depth should be considered when computing the SOC stocks for a given area, many previous estimates of SOC stocks at global (Eswaran et al., 1993), national (Chhabra et al., 2003; Guo et al., 2006), regional (Yu et al., 2007) and watershed (Shrestha et al., 2004) scales, were computed by multiplying the mean C concentration, bulk density and area. These estimates did not account for the spatial variability of SOC concentration within the soil (Mishra et al., 2009) and may thus be of low reliability (Meersmans et al., 2008). The recent developments in geostatistics, artificial neural network and multiple regression have been used to account for the spatial variability of SOC and can improve digital soil mapping (DSM) considerably (Mishra et al., 2009). DSM at plot (Simbahan et al., 2006), watershed (Minasny et al., 2006) and regional (Meersmans et al., 2008) scales, has shown its potential for SOC mapping (Minasny et al., 2013). However, there is hardly any DSM of SOC done at different depths and under different LULC types, especially in the Himalayan region. Although moderate in extent, the Himalayan region is a globally important C sink and therefore the gaps in our data and knowledge of its SOC need to be filled (Shrestha et al., 2004; Sitaula et al., 2004; Singh et al., 2011). This study aimed to characterize SOC in montane ecosystems of Bhutan in the Eastern Himalayas, and particularly to: (i) estimate SOC density and SOC stocks under different LULC types (ii) model the spatial distribution of SOC density and SOC stocks (iii) and establish a baseline data on SOC stocks for future studies of SOC dynamics.

2. Materials and method

2.1. Study area

The study area (1014 km^2) covers much of the Paro valley, a sub-catchment in the Wang Chhu watershed in western Bhutan (Fig. 1). The rugged mountainous landscape is characterized by deep valleys, gorges and high peaks. Altitudes range from 1769 to 5520 m above sea level (asl), within a distance of 65 km. The climate is monsoonal and varies with altitude from warm temperate in the valleys to alpine on the upper slopes and ridges. Mean monthly temperatures in the valleys range from about 10 °C in January to 24 °C in July. Annual average precipitation varies with altitude and landscape position and ranges from 600 mm in the southern part to 2900 mm in the north (Source: Hydromet Services Division, Ministry of Economic Affairs, Thimphu, Bhutan). The complex variability of precipitation in the study area and in the Himalayas in general, is demonstrated by the short range variation in such a given single valleys, with wetter zones at mid-altitude (3000–4000 m asl) interposed between drier valley floors and upper slopes.

The area is underlain by the metasedimentary unit of the Greater Himalaya in the north and the Paro Formation of the Lesser Himalaya in the south (Long et al., 2011). The metasedimentary unit consists of paragneisses, muscovite-biotite-garnet schist, and quartzite while the Paro Formation is largely dominated by quartzite, quartzite-garnet-schist, marble, and minor calc-silicate rocks (Tobgay et al., 2010). These rocks were formed as a result of intense tectonic activity. The mountains are young and still rising, leading to landscape dissection and natural soil erosion (Singh et al., 2010); the latter process is continually affecting soil development. There are four main altitudinally determined soil zones: (i) moderately weathered and leached thin dark topsoil over bright subsoil up to about 3000 m asl; (ii) very bright orange-colored non-volcanic andosolic soils and (iii) acidic soils with thick surface litter that grade to weak podzols up to about 4000 m asl; and (iv) alpine turf with deep dark and friable topsoil over yellowish subsoil mixed with raw glacial deposits above 4000 m asl (Baillie et al., 2004). The valleys are characterized by narrow alluvial floors, fans and terraces, with the lower slopes and alluvia often mantled with colluvia from upslope and aeolian deposits (Baillie et al., 2004; Caspari et al., 2006; Dorji et al., 2009).

More than 65% of the Bhutan's population depends on agriculture, livestock and forestry for their livelihood. However, agricultural land accounts for only about 3% of the total land area due to the rugged terrain and extreme climatic conditions. About 72% of the country is under forest cover (LCMP, 2010). The study area is more intensively used, but still has about 73% under forest and only 7% in agricultural production. The dominant LULC types are mixed coniferous forest (MCF, 36.4% of the study area), blue pine forest (BPF, 23.7%), broadleaf (BF, 8.1%), fir forest (FF, 5.0%), shrubs (SH, 13.7%), grassland (GL, 2.8%), dry land (DL, 4.2%), paddy land (PL, 1.8%) and orchards (HO, 1.0%). Small and inaccessible patches of open water, snow and bare rock cover about 3.5% (36 km^2) of the study area and are not included in this study.

2.2. Acquisition and derivation of environmental covariates

To obtain the digital terrain attributes required as covariates for DSM, a 90 m resolution digital elevation model (DEM) covering the study area was extracted from the Shuttle Radar Topography Mission (SRTM) elevation data portal (http://earthexplorer.usgs.gov/-available on August 30, 2013). Slope gradient, aspect, curvatures (profile and plan), SAGA wetness index (SWI), terrain ruggedness index (TRI) and multi-resolution index for valley bottom flatness (MrVBF) were derived from the DEM using the System for Automated Geoscientific Analysis (SAGA) software (http://www.saga-gis.org/en/index.html). Based on Moore et al. (1993), who characterized terrain-determined spatial variations in soil moisture content by a terrain index, the SWI was computed as a tangent function of slope angle β and modified specific catchment area (SCA_M) (Böhner and Selige, 2006) (Eq. (1)). The SCA_M is a function of slope angle β and the neighboring maximum values SCA_{max} (Eq. (2)).

$$\mathrm{SWI} = \ln(\mathrm{SCA}_M/\tan\beta) \tag{1}$$

$$\mathrm{SCA}_M = \mathrm{SCA}_{\max}(1/15)^{\beta\exp(15^\beta)} \quad \text{for SCA} < \mathrm{SCA}_{\max}(1/15)^{\beta\exp(15^\beta)} \tag{2}$$

where *SCA* is the specific catchment area defined as the corresponding drainage area per unit contour width (m^2 m^{-1}) (Böhner and Selige, 2006). The TRI indicates elevation difference between adjacent cells of a digital elevation grid. The process basically calculates the difference in elevation values from a center cell and the eight cells immediately surrounding it. It squares each of the eight elevation difference values to make them all positive and averages the squares. The TRI is then derived by taking the square root of this average, and corresponds to average elevation change between any point on a grid and its surrounding area (Riley et al., 1999).

$$\mathrm{TRI} = Y\left[\sum (x_{ij} - x_{00})^2\right]^{1/2} \tag{3}$$

where x_{ij} = elevation of each neighbor cell to cell (0,0). MrVBF quantifies the depositional area in a landscape. It is a function of slope and elevation to classify valley bottoms as flat, and low areas through a series of neighborhood operations at progressive coarser