Digital Soil Mapping of Soil Organic Carbon Stock in Bhutan

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ABSTRACT

Soil organic carbon (SOC) plays an integral part in improving soil security, water security, food security, energy security, climate change abatement, biodiversity protection, and ecosystem services. It is important to understand its stock and spatial distribution for better management. However, not many countries have managed to map their national SOC stock and Bhutan is no exception. There is paucity of SOC information to clearly formulate plans and programs to increase Carbon (C) sequestration and enhance SOC storage in the country. A preliminary mapping of SOC stock of Bhutan for the top 30 cm depth was carried out to establish a baseline and contribute to global SOC mapping. A total of 993 data points was used for mapping SOC stock using regression kriging (RK). Regression tree model and ordinary kriging were used to perform the RK with elevation, land use land cover (LULC), slope, aspect, profile and plan curvatures, normalized difference vegetation index, SAGA wetness index, mean precipitation, mean temperature, geology, and terrain ruggedness index as environmental covariates. The model validation was done by repeated data splitting method. Preliminary results show that for the top 30 cm depth, Bhutan stores about 0.4 giga tonne carbon (GtC) with SOC density ranging from 0.5 to 315.3 ton ha^{-1}. Among the environmental covariates, LULC, topography, and climatic factors had significant influence on SOC stock and its spatial distribution. SOC stock was relatively low in the southern and eastern regions as opposed to the western and northern parts of the country. Under different LULC types, the SOC stock was lowest under agriculture land and highest under forest. These results are based on a small set of soil data and must be used with caution. However, for better SOC stock estimation and mapping, more and well distributed soil data will be necessary.

Keywords: *Soil Organic Carbon, Mapping, Land use land cover*

1. Introduction

Soil is essentially made up of minerals, organic carbon, water, and air. Among these four main components, soil organic carbon (SOC) forms the integral part of a functional soil. This is largely because SOC has the ability to improve the soil physical, chemical, and biological properties, which can enhance soil security. Enhanced soil security can improve food security, water security, energy security, climate stability, biodiversity, and ecosystem services (McBratney, Field & Koch, 2014). SOC also plays a key role in global carbon (C) cycle as it is

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the largest terrestrial C pool. Because of the important role it plays, SOC is often considered as a common indicator for soil security, water security, and ecosystem services. Further, SOC stock is one of the three indicators in assessing Land Degradation Neutrality (LDN) status by 2030. Bhutan being an LDN member country, information on SOC stock and its spatial distribution will be vital to assess its LDN status.

Globally, soil stores about 1500 GtC (1 GtC = 10^{15}gC) in the top one meter (Jobbágy & Jackson, 2000) which is approximately three times as much C found in the biosphere and twice as much C found in the atmosphere. For the top 30 cm depth, it stores about 680 GtC (FAO, 2017). Assuming that other components of global C cycle remain constant with current CO_2 concentration of 390 ppm, a change in global SOC storage by 1% may trigger a shift of about 8 ppm of CO_2 concentration in the atmosphere (Baldock, Wheeler, McKenzie & McBretney, 2012). This highlights the significance of C sequestration and storage in the soil to mitigate climate change. In order to enhance C sequestration and C storage, adequate information on SOC is necessary to formulate appropriate land management and C sequestration strategies. However, such information is limited in most of the countries, particularly in developing countries. This has posed a challenge to land managers in improving soil quality, increasing resilience to climate change, and enhancing ecosystem services through better SOC management.

The National Soil Services Centre (NSSC) under the Ministry of Agriculture and Forests made its first attempt to produce the SOC stock map of Bhutan for the top 30 cm depth with 993 observed data using digital soil mapping (DSM) techniques. The DSM of SOC stock of Bhutan was done with the objectives to set up a national baseline on SOC stock and contribute to global SOC stock mapping and formulate better C sequestration and SOC management strategies in the country.

2. Materials & Method

2.1. Study area

Bhutan is a landlocked country located in the Himalayas with China in the north and India in the east, west, and south. It has a geographical area of 38,394 km^2 with rugged terrain characterized by 'V' shaped valleys and high peaks. 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 (Baillieet al., 2004; Caspariet al., 2006; Dorjiet al., 2009). Within less than 200 km (south-north), the altitudinal gradient increases from about 97 m to about 7570 m above sea level (masl). As such, there exist several agro-ecological zones with distinct climatic regimes in between. Monsoon dominates the climatic condition with annual precipitation varying from more than 2000 mm in the south to less than 1000 mm in the north and central parts of the country. The mean annual temperature ranges from approximately 14° to 26° C during summer and about -3° to 15° C in winter.

The Himalayan Mountains are young and still rising, leading to landscape dissection and natural soil erosion (Singh, Singh & Skutsch, 2010); the latter process is continually affecting soil development. There are four main soil zones grouped based on altitude i.e. i) moderately weathered and leached thin dark topsoil over bright subsoil up to about 3000 masl; ii) very bright orange-coloured 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 masl (Baillie et al., 2004).

More than 58% of Bhutan's population depends on agriculture, livestock and forestry for their livelihood. However, the cultivated agricultural land accounts only for about 3% of the total land area (LCMP, 2010) due to rugged terrain and extreme climatic conditions. As such, more than 70% of the total agriculture land is located on steep slopes with high incidence of soil erosion. On the other hand, about 71% of the country is under forest cover (LCMP, 2010) with very rich biodiversity. As expected, the spatial variation of different LULC types is greatly influenced by altitude, slope, and climatic regimes. As presented in Figure 1, broadleaf forest is predominant below 2500 masl with coniferous forest between 2500m and 3500 masl. However, shrubs and grassland occur all along the altitudinal gradient. As anticipated, snow and screes are largely confined to areas above 3500 masl. Conversely, agriculture land is mostly located on valley bottoms and mountain foot slopes.

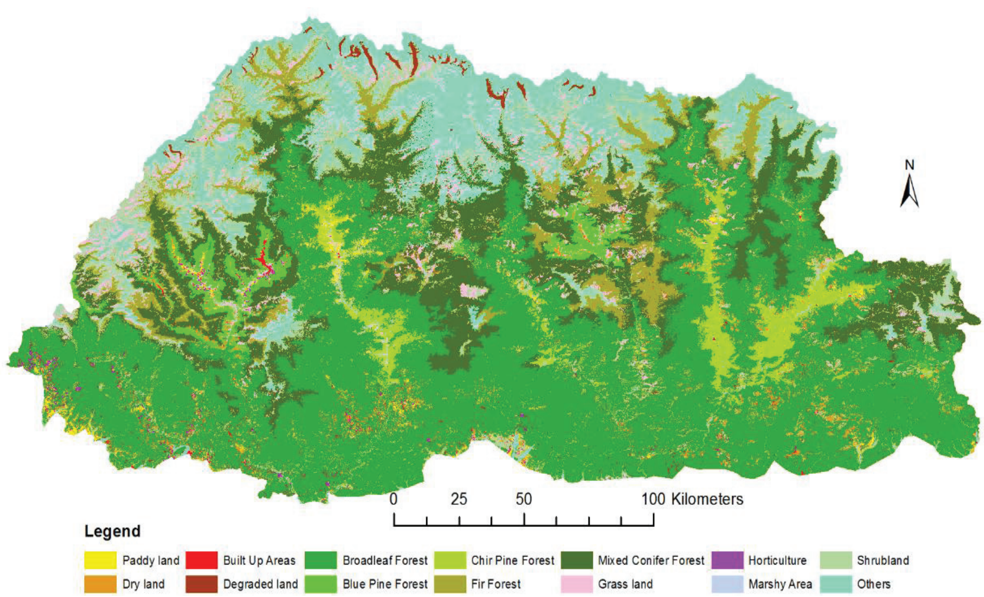

Figure 1.LULC map of Bhutan (LCMP, 2010)

2.2. Soil data

Soil information is limited in Bhutan as not many soil surveys have been done to date. As such, its soil resources are basically unexplored and not well documented. For this SOC mapping exercise, a total of 993 data points, from previous soil surveys (1997-2017), was used (Figure 1). About 80% of the total data points were from soil profile pits while the remaining data points were from auger bore holes. Soils were described and sampled based on genetic horizons. Samples were analysed for various soil parameters including carbon (C) concentration using (Walkley & Black, 1934) and bulk density using core ring method (Blake, Hartge & Klute, 1986).

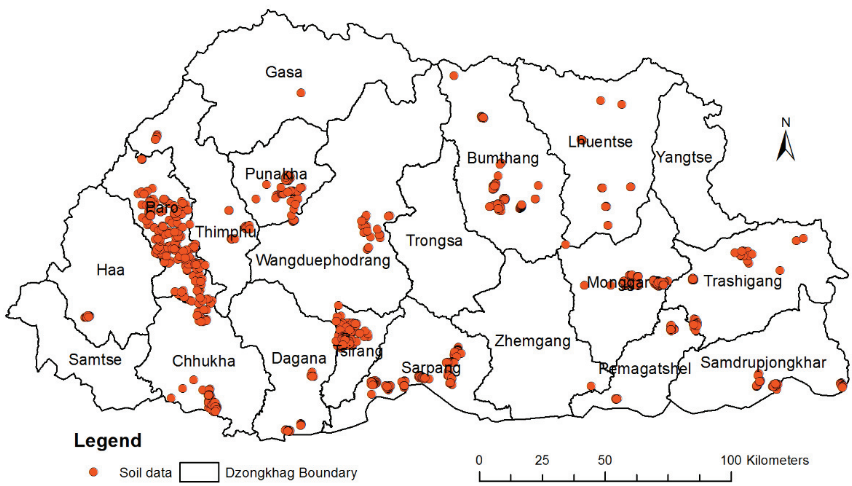

Figure 1.Distribution of soil observation sites

Since soil samples were collected based on genetic horizons, they had different soil depths and this posed a challenge to digitally map SOC stock for a particular soil depth. In this regard, an equal-area spline function was fitted to the profile values of the target soil variables using the CSIRO Spline Tool V2 (ASRIS, 2011) to convert the horizon-based values to the desired soil depth (0-30 cm). The equal-area spline function is based on the quadratic spline model of (Bishop, McBratney & Laslett, 1999).

2.3. Acquisition and derivation of environmental covariates

Digital Soil Mapping (DSM) of any soil property hinges on the use of easily discernible ancillary soil and/or environmental attributes. To generate the terrain attributes a 30 m digital elevation model (DEM) covering whole Bhutan was extracted from the Shuttle Radar Topography Mission (SRTM) elevation data portal (http://earthexplorer.usgs.gov) and was re-sampled to 1 km resolution. Slope gradient, aspect, slope curvatures (profile and plan), SAGA wetness index (SWI), and terrain ruggedness index (TRI) were derived from the DEM using the System for Automated Geo-scientific Analysis (SAGA) software (http://www.saga-gis.org/en/index.html) and Arc GIS software (version 10.3). In addition to the above covariates, the LULC data (LCMP, 2010), geological map (GEO) - Department of Geology and Mines), mean temperature and precipitation (www.worldclim.org), and normalized difference vegetation index ($NDVI$) were used as covariates after re-sampling to 1 km resolution.

2.4. Spatial modelling of SOC concentration and bulk density

Digital Soil Mapping (DSM) of any soil property is done with the assumption that a soil property of interest is closely associated with easily discernible ancillary environmental variables. This enables the target variable to be predicted by establishing relationships between it and the ancillary variables (McBratney et al., 2003). Based on this assumption, several methods have been used to digitally map the target variable. (Odeh, McBratney & Chittleborough, 1995) compared several methods of DSM: multi-linear regression, ordinary kriging, universal kriging, isotopic co-kriging, heterotopic co-kriging, and some variants of regression kriging (RK) models, and found that RK model to be most superior. A later study by Minasny and McBratney (2007) reported RK model to be more practical and robust than other prediction models. We used RK to digitally map the SOC stock.

RK has two main components i.e. regression and kriging (Figure 2). For the regression part, regression tree model (RTM) was used (Cubist 2.09 package) with elevation (DEM), LULC, slope, aspect, profile and plan curvatures, NDVI, SWI, mean precipitation, mean temperature, geology and TRI as covariates to predict the target variable. The RTM is found to be robust and appropriate for complex landscapes, such as in the Himalayas. The RTM is a non-parametric prediction model, which predicts the target variable based on linear regression models instead of discrete values predicted by the classical tree models (Minasny & McBratney, 2008).

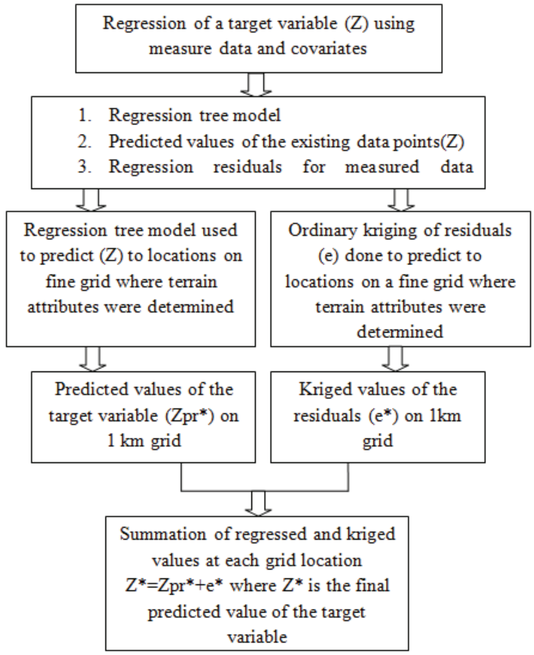

Figure 2.Flow chart showing the steps of RK for DSM (adapted from Odeh et al. (1995)).

At each node of the tree model, conventional linear least-squares regression is used to create the model associated with each of the terminal rules. Thus, the model generates a set of comprehensible rules, each of which has an associated multivariate linear model. When the rule conditions are met, the model predicts the target variable for each grid cell that has values for the appropriate predictor covariates (Minasny & McBratney, 2008). For the kriging part, the residuals, which are the difference between the measured and regressed values, were interpolated onto the entire 1 km grid, using a simple kriging, embedded in the package: Variogram Estimation and Spatial Prediction plus Error (VESPER) (Minasny, McBratney & Whelan, 2005). The final predicted value of the target variable at each 1 km grid cell was computed by summing up the regressed value from the RTM and the kriged residual (Figure 2).

2.5. Data validation

Any prediction model needs to be validated to assess its accuracy and reliability. It can be done either through external or internal validation. The former uses a new validation dataset from the same or similar population for validating previous models and is considered to be relatively better than internal validation methods. However, the difficulty in obtaining a new independent external dataset forces to go for internal validation. Repeated data splitting is a common internal validation method and we used this to validate our models. The whole data was partitioned into two portions, called the training and validation datasets. The training dataset constituted 70% of the total data points (698 points) and was selected through a simple random sampling procedure.The remaining 30% data was used as a validation dataset. Firstly, RTM was fitted onto the training dataset (using Cubist 2.09) and the model was used to predict the target variable for the validation dataset. Secondly, the residuals for the training dataset were calculated by subtracting the regressed values from the measured values of the target variable. Thirdly, the residuals of the training dataset were kriged to predict the residuals of the validation dataset using VESPER. The final RK predictions for the validation dataset was obtained by summing the regressed values from RTM and kriged values (Figure 2). The performance of the RK model was assessed by plotting the predicted values with measured values of the validation dataset. This whole process was repeated for 10 times to assess the stability of the prediction accuracy of the RK model. At each iteration, the statistical parameters including: (i) root mean square error (RMSE), (ii) coefficient of correlation (*R*), (iii) coefficient of determination (R^2), and (iv) mean error (ME) were determined and averaged at the end to provide the overall prediction accuracy of the model. The RMSE, which provides a measure of accuracy of the prediction method, is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=i}^{n}\left[z(s_j) - z^*(s_j)\right]^2} \qquad (1)$$

and the ME (Odeh et al., 1995), which measures bias of prediction, is defined as:

$$\mathrm{ME} = \frac{1}{n}\sum\left[z(s_j) - z^*(s_j\right. \qquad (2)$$

where $z(s_j)$ and $z^*(s_j)$ are the observed and predicted values, respectively (Eq. 1 and 2). For more accurate prediction, the RMSE should be as small as possible while the ME should be close to zero.

2.6. Computing SOC stock

Although SOC density and SOC stock are often used interchangeably in literature (Minasny *et al.*, 2006), they differ in scale and unit (Dorji *et al.*, 2014). SOC density is the SOC mass per unit area for a given depth, which can be calculated as:

$$SOC_d(kgm^{-2}) = SOC(kg/kg) * BD\ (kgm^{-3}) * D(m) \qquad (3)$$

where SOC_d is SOC density (kg m^{-2}), SOC is SOC concentration (kg/kg), BD is bulk density (kg m^{-3}) and D is depth interval thickness (m). On the other hand, SOC stock is the actual SOC mass for a given soil depth and area. It was calculated by summing up the product of SOC density and area of the smallest mapping unit e.g. grid cell 1 × 1km^2.

$$SOC_{st}(t) = \sum_{i=1}^{n}(SOC_{di} * A_i)/10^3 \qquad (4)$$

where SOC_{st} is SOC stock in metric tonne (t), n is number of 1 km grid cells, SOC_{di} is SOC density of grid cell for a particular depth interval (kg m^{-2}), A_i is an area of 1 km grid cell (1km^2) and 10^3 is the unit conversion factor.

3. Results and Discussion

3.1. Spatial modelling of SOC concentration and bulk density

As shown in Table 1, the RTM based on the whole dataset (993 data), used MT, GEO, NDVI, PLCUR, slope, ASP, MP, and ALT as conditions to perform the regression for SOC concentration. However, MP, MT, ALT, NDVI, TRI, slope, ASP, SWI, PLCUR, and PRCUR were used as covariates. Similarly, for bulk density, MP, ALT, SWI, MT, PRCUR, NDVI and ASP were used as conditions and MT, MP, ALT, NDVI, TRI, SWI, slope, PRCUR, PLCUR, and ASP as covariates. Among the environmental covariates, MP, MT, ALT, and NDVI showed more influence on both SOC concentration and bulk density, and their spatial distributions (Table 1).

Table 1.Usage (%) of covariates in the RTM for predicting SOC concentration and bulk density

Attribute usage	For SOC Concentration (0-30 cm depth)			
Conditions (Usage in %)	MT (99%)	GEO (72%)	NDVI (43%)	PLCUR (32%)
	Slope (25%)	ASP (24%)	MP (13%)	ALT (9%)
Environmental covariates used in regression tree model (Usage in %)	MP (89%)	MT (86%)	ALT (70%)	NDVI (60%)
	TRI (57%)	Slope (48%)	ASP (46%)	SWI (41%)
	PLCUR (14%)	PRCUR (11%)		
Attribute usage	For Bulk density (0-30cm depth)			
Conditions (Usage in %)	MP (75%)	ALT (49%)	SWI (45%)	MT (32%)
	PRCUR (12%)	NDVI (9%)	ASP (8%)	
Environmental covariates used in regression tree model (Usage in %)	MT (99%)	MP (95%)	ALT (91%)	NDVI (81%)
	TRI (74%)	SWI (67%)	Slope (62%)	PRCUR (31%)
	PLCUR (20%)	ASP (13%)		

TRI terrain ruggedness index, SWI SAGA wetness index, NDVI normalized difference vegetation index, MT mean temperature, MP mean precipitation, ASP aspect, PLCUR plain curvature, PRCUR profile curvature, ALT altitude, GEO geology.

Overall, the RTM performed well as indicated by low average error (AE) and ME for both SOC concentration and bulk density (Table 2). The AE was 0.89 g/100 g for SOC concentration and 0.05 g cm^{-3} for bulk density. The relative errors (RE) for both SOC concentration and bulk density were less than 1. The coefficient of determination (R^2) was moderately high for both SOC concentration (0.59) and bulk density (0.88). Looking at R^2 and ME values, the RTM was more robust and less bias in predicting bulk density than SOC concentration. This could be attributed to less spatial variation of bulk density compared to SOC concentration.

Table 2.Overall performance of RTM in predicting SOC concentration and bulk density

Depth (cm)	SOC (g/100g)					Depth (cm)	Bulk density (g cm^{-3})				
	AE	RE	ME	RMSE	R^2		AE	RE	ME	RMSE	R^2
0 - 30	0.89	0.61	0.005	1.34	0.59	0 - 30	0.05	0.23	0.0001	0.09	0.88

SOC soil organic carbon, AE average error, RE relative error, ME mean error, RMSE root mean square error, R^2 coefficient of determination

3.2. Validation of RTM and RK models

The overall performance of RTM and RK, in predicting SOC concentration and bulk density, was done using the repeated data splitting method. Based on the statistical parameters presented in Table 3 and 4, both RTM and RK performed better in predicting bulk density than SOC concentration. However, when compared between RTM and RK models, RK was supper in predicting both SOC concentration and bulk density with relatively low ME and RMSE and high coefficient of determination (R^2) (Table 3 & 4). Thus, RK was used to digitally map SOC stock.

Table 3.Performance of RTM in predicting SOC concentration and bulk density

Depth (cm)	SOC (g/100g)					Depth (cm)	Bulk density (g cm^{-3})				
	AE	RE	ME	RMSE	R^2		AE	RE	ME	RMSE	R^2
0 - 30	0.82	0.57	0.11	1.49	0.44	0 - 30	0.04	0.17	0.002	0.11	0.85

ME mean error, RMSE root mean square error, R^2 coefficient of determination

Table 4.Performance of RK in predicting SOC concentration and bulk density

Depth (cm)	SOC (g/100g)			Depth (cm)	Bulk density (g cm^{-3})		
	ME	RMSE	R^2		ME	RMSE	R^2
0 - 30	0.05	1.43	0.46	0 - 30	0.001	0.10	0.85

ME mean error, RMSE root mean square error, R^2 coefficient of determination

3.3. SOC density under different LULC types

Since SOC density provides better information for SOC storage than SOC concentration, SOC density (1×1 km^2 grid) was computed by multiplying RK predicted SOC concentration with bulk density (Eq. 1). Figure 3 shows relatively low SOC density in the valley bottoms where most of the agriculture fields are located. However, the upper slopes, which are mostly under forest, shrubland and grassland, have comparatively high SOC density. This indicates a strong influence of LULC and landform on the spatial distribution of SOC density. Under different LULC types, the mean SOC density for the upper 30 cm depth decreased in the order of mixed conifer forest> fir forest> others> grassland> shrubland> blue pine forest> marshy land> horticulture> dry land> paddy land> built-up areas> chirpine forest (Table 4). This is in line with the results reported by (Dorji, Odeh, Field & Baillie, 2014).

Table 4.Predicted SOC density under different LULC types (0-30 cm depth)

Sl #	LULC type	Mean SOC (t/ha)	Sl#	LULC type	Mean SOC (t/ha)	Sl#	LULC type	Mean SOC (t/ha)
1	Paddy land	62.16	6	Blue Pine Forest	84.79	11	Horticulture	71.58
2	Dry land	64.05	7	Chir Pine Forest	51.54	12	Marshy Area	74.1
3	Built Up Areas	60.52	8	Fir Forest	102.35	13	Shrubland	92.49
4	Degraded Land	81.75	9	Mixed Conifer Forest	105.21	14	Others	101.42
5	Broadleaf Forest	75.35	10	Grassland	98.26			

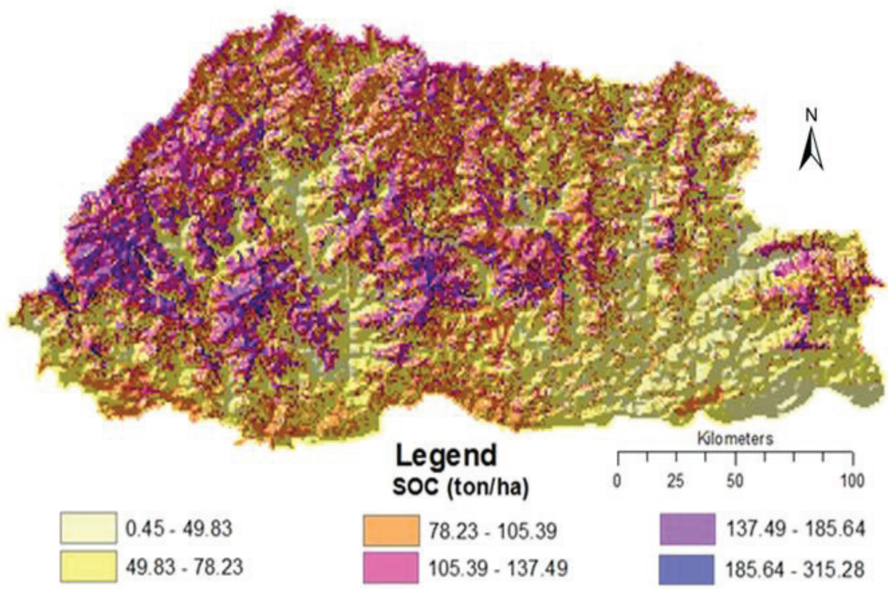

Figure 3.Predicted SOC density (1×1 km^2 grid) for the top 30 cm depth

The SOC stock for each grid was computed (Eq. 2) and added to estimate the overall SOC stock for the entire country. The preliminary results show that for the top 30 cm depth, Bhutan stores about 0.4 GtC with SOC density ranging from 0.45 to 315.28 ton ha^{-1}. The SOC stocks in the southern and eastern regions are relatively small as opposed to the western and northern parts of the country (Fig. 3). This is chiefly due to less forest cover and high rate of mineralization in the eastern and southern regions, respectively. The SOC stock under different LULC types was quite similar to what (Dorji et al., 2014) reported with SOC stock lowest under agriculture land and highest under forest.

4. Conclusion

The preliminary results show that Bhutan stores about 0.4 GtC in the top 30 cm depth. But the challenge now is how to maintain it against the backdrop of increased land degradation, unsustainable land management, and climate change. In this regard, land and land-based natural resources should be sustainably managed to reduce C emission and increase C sequestration. Furthermore, appropriate plans and policies need to be put in place to combat land degradation and increase SOC storage to mitigate climate change and enhance ecosystem services. This is the first attempt made to map SOC stock in Bhutan (0-30 cm depth) using DSM techniques. Since a small dataset was used for mapping SOC stock, the results presented here may not be very accurate and comprehensive. Hence, the information on SOC density and SOC stock should be used with caution. For more accurate and reliable SOC stock estimation and mapping, more and evenly distributed soil data is necessary. Furthermore, the capacity of the national staff on DSM needs to be developed.

References

ASRIS. (2011). ASRIS - Australian Soil Resource Information System. http://.asris.csrio.au. Accessed November 7, 2012.

Baillie, I. C., Tshering, K., Dorji, T., Tamang, H. B., Dorji, T., Norbu, C. (2004). Regolith and soils in Bhutan, Eastern Himalayas. *European Journal of Soil Science, 55*(1), 9-27. doi:10.1046/j.1365-2389.2003.00579.x

Baldock, J. A., Wheeler, I., McKenzie, N., & McBrateny, A. (2012). Soils and climate change: potential impacts on carbon stocks and greenhouse gas emissions, and future research for Australian agriculture. *Crop and Pasture Science, 63*(3), 269-283. doi:http://dx.doi.org/10.1071/CP11170

Bishop, T. F. A., McBratney, A. B., & Laslett, G. M. (1999). Modelling soil attribute depth functions with equal-area quadratic smoothing splines. *Geoderma, 91*(1–2), 27-45. doi:http://dx.doi.org/10.1016/S0016-7061(99)00003-8

Blake, G. R., Hartge, K. H., & Klute, A. (1986). Bulk density. *Methods of soil analysis. Part 1. Physical and mineralogical methods. SSSA Book Series*, 363-375.

Caspari, T., Bäumler, R., Norbu, C., Tshering, K., & Baillie, I. (2006). Geochemical investigation of soils developed in different lithologies in Bhutan, Eastern Himalayas. *Geoderma, 136*(1–2), 436-458. doi:10.1016/j.geoderma.2006.04.017

Dorji, T., Caspari, T., Bäumler, R., Veldkamp, A., Jongmans, A., Tshering, K. (2009). Soil development on Late Quaternary river terraces in a high montane valley in Bhutan, Eastern Himalayas. *CATENA, 78*(1), 48-59. doi:10.1016/j.catena.2009.02.018

Dorji, T., Odeh, I. O. A., Field, D. J., & Baillie, I. C. (2014). Digital soil mapping of soil organic carbon stocks under different land use and land cover types in montane ecosystems, Eastern Himalayas. *Forest Ecology and Management, 318*(0), 91-102. doi:http://dx.doi.org/10.1016/j.foreco.2014.01.003

FAO (Cartographer). (2017). Global Soil Organic Carbon Map

Jobbágy, E. G., & Jackson, R. B. (2000). The vertical distribution of soil organic carbon and its relation to climate and vegetation. *Ecological Applications, 10*(2), 423-436.

LCMP. (2010). Land cover mapping project. Technical Report. Ministry of Agriculture and Forests, Royal Government of Bhutan, Thimphu. http://www.nssc.gov.bt/bhutan-land-cover-assessment-2010 (accessed on 29 September 2012).

McBratney, A., Field, D. J., & Koch, A. (2014). The dimensions of soil security. *Geoderma, 213*, 203-213.

McBratney, A. B., Mendonça Santos, M. L., & Minasny, B. (2003). On digital soil mapping. *Geoderma, 117*(1–2), 3-52. doi:10.1016/s0016-7061(03)00223-4

Minasny, B., & McBratney, A. B. (2007). Spatial prediction of soil properties using EBLUP with the Matérn covariance function. *Geoderma, 140*(4), 324-336. doi:http://dx.doi.org/10.1016/j.geoderma.2007.04.028

Minasny, B., & McBratney, A. B. (2008). Regression rules as a tool for predicting soil properties from infrared reflectance spectroscopy. *Chemometrics and Intelligent Laboratory Systems, 94*(1), 72-79. doi:http://dx.doi.org/10.1016/j.chemolab.2008.06.003

Minasny, B., McBratney, A. B., Mendonça-Santos, M. L., Odeh, I. O. A., & Guyon, B. (2006). Prediction and digital mapping of soil carbon storage in the Lower Namoi Valley. *Soil Research, 44*(3), 233-244. doi:http://dx.doi.org/10.1071/SR05136

Minasny, B., McBratney, A. B., & Whelan, B. M. (2005). VESPER version 1.62. Australian Centre for Precision Agriculture, McMillan Building A05, The University of Sydney, NSW 2006. http://www.usyd.edu.au/su/agric/acpa (accessed on 1st July 2012).

Odeh, I. O. A., McBratney, A. B., & Chittleborough, D. J. (1995). Further results on prediction of soil properties from terrain attributes: heterotopic cokriging and regression-kriging. *Geoderma, 67*(3–4), 215-226. doi:10.1016/0016-7061(95)00007-b

Singh, S. P., Singh, V., & Skutsch, M. (2010). Rapid warming in the Himalayas: ecosystem responses and development options. *Climate and Development, 2*(3), 221(212).

Walkley, A., & Black, I. A. (1934). An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. *Soil Science, 37*(1), 29-38. doi:10.1097/00010694-193401000-00003