Modelling Soil Organic Carbon Stocks Under Commercial Forestry in KwaZulu-Natal South Africa Using Topo-Climate Variables

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Abstract
Commercial forests (CFs) are expanding globally, offering great potential for absorbing carbon and mitigating climate change. Compared to natural forests (NFs), CFs landscapes are largely ignored in soil organic carbon (SOC) mapping and climate change mitigation. Specifically, the relationship between the controlling factors that include topo-climate variables and the distribution of SOC is still poorly understood. Consequently, this study sought to map SOC stock variability within CFs using topo-climatic variables and geospatial strategies. Eighty one soil samples and 31 topo-climate predictors were simulated for SOC. A backward elimination method and the Maximum Entropy (Maxent) algorithm were used for optimum variable selection (11 variables) and regression, respectively. Results showed good accuracies for both training (area under the curve = 0.906) and test (area under the curve = 0.885) datasets, and provide an effective framework for SOC modelling within CFs; valuable for climate change mitigation.

Keywords: Commercial forests; Soil Organic Carbon; Topo-climate; Maxent.

Introduction

Commercial forests (CFs) constitute a vast reservoir of carbon with immense potential for reducing net greenhouse gas emissions (IPCC 2016). From 1990 to 2015, the carbon held by CFs was comparable to that of natural forests (1.08 vs. 1.44 gigaton CO2 yr1), and recent projections predict that CFs will increase by 20 to 50% by 2030 (FAO 2010). Forest soils are the largest carbon reservoir, consequently, soils under CFs could store large amounts of carbon as soil organic carbon (SOC). However, whereas SOC within natural forests (NFs) have been extensively studied, the SOC distribution within CFs is still poorly understood. Additionally, SOCs under CFs are dynamic and dependent on a wide range of environmental factors such as climate and topography. Hence, knowledge on SOC variability and the controlling environmental factors plays an essential role in assessing regional and global carbon balances as well as examining the feedback from the terrestrial ecosystem to climate change. Such knowledge is also useful for developing suitable management strategies to achieve the objectives of the Intergovernmental Panel on Climate Change (IPCC) and Kyoto protocol. Geospatial techniques offer a more practical and economical means of modeling SOC at local, regional and global scales compared to field and laboratory determination methods. This has been facilitated by the multiplication of image datasets capable of generating spatially continuous topo-climate metrics that affect SOC distribution (Li et al 2018). In this study, we used a geospatial strategy to predict SOC stocks under commercial forests in KwaZulu-Natal, South Africa.

Methodology

The study was conducted in KwaZulu-Natal province South Africa with about 1.4 million hectares of CFs cover. Field data were collected during the rainy summer season using a stratified random sampling method across low, medium and high productivity areas based on prior knowledge of the CFs stands. A total of 81 sample plots were taken at a depth of 30cm using soil auger and analyzed in the laboratory for SOC concentration using dichromate oxidation method. Thirty one environmental variables (topography and climate) were derived from 30m resolution SRTM-DEM and WorldClim datasets archives (http://www.worlclim.org/); and used as predictors to SOC. A backward elimination method was used to select 11 optimum variables and Maxent model was used for regression by dividing the data into a train (70%) and test (30%) data. The area under curve (AUC) was used as an evaluation metric and ranges between 0 and 1. Thus the higher the AUC, the higher the accuracy.

Results and discussion

Figure 1 shows SOC distribution map and the accuracy of both the train and test data based on Maxent. Both the train and test data indicated a high AUC of 0.906 and 0.885, respectively. A jackknife function is used in the maxent model to determine how each predictor contributes to the overall model. Rainfall (30.2%) contribute the largest portion, followed by temperature (22.9%), slope (16.1%), elevation (11.6%), and topographic wetness index (8.9%); totaling over 89%. Direct insolation (3.1%), catchment area (2.9%), positive openness (1.8%), aspect (1.1%), profile curvature (0.8%) and longitudinal curvature (0.6%) had the least impact. A number of previous studies have shown that rainfall, temperature, slope, elevation, and topographic wetness index (TWI) affect the distribution of SOC. Rainfall and TWI have a profound effect on soil moisture and hydrological processes that play a critical role in SOC cycling. Temperature also influences soil moisture and relative humidity critical for the amount of rainfall within a landscape. Slope and elevation influences soil erosion and vegetation growth due to optimal soil development conditions that may include erosion of nutrient-rich topsoil from higher grounds that are deposited in low lying areas. Generally, areas of higher rainfall, temperature and TWI has a higher SOC content. In contrast, higher SOC content is found in lower slope and elevation areas. Furthermore, results show that climatic variables significantly contribute more to SOC variability than topographic variables in the area (Li et al 2018).

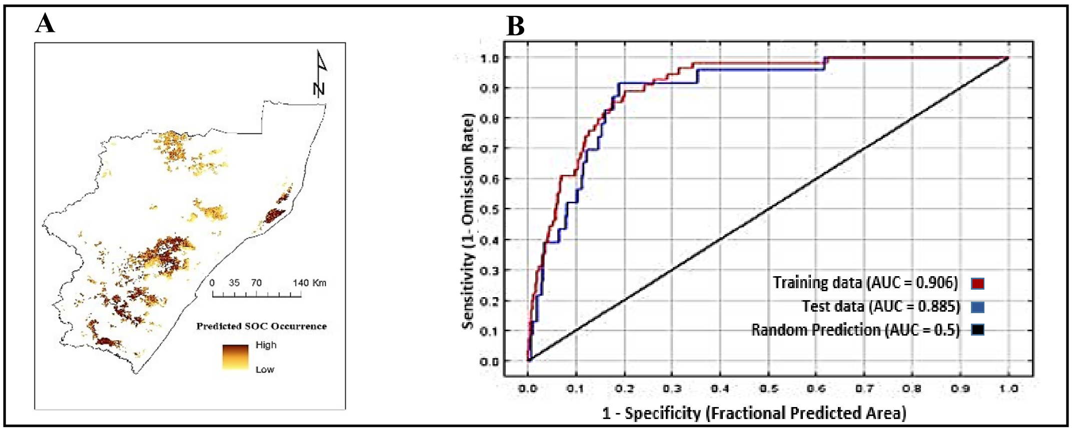

Figure 1. (A) Spatial distribution of SOC under commercial forests in KwaZulu-Natal, South Africa, (B) Accuracy metrics for the train, test and random prediction represented in red, blue and black respectively.

Conclusion

This study investigated the impact of environmental variables on SOC distribution under commercial forestry using the Maxent algorithm. The results showed high accuracy, with rainfall contributing the most to the model while longitudinal curvature contributed the least. Results are important to achieve national carbon accounting and also valuable to forest managers, ecologist and relevant stakeholders in understanding the spatial distribution of SOC within CFs compartments.

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