Soil Organic Carbon Loss Estimation Following Reclamation of Picea schrenkiana Forest Land on the Northern Slope of the Tianshan Mountains: Postprint

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Abstract

In the context of global warming, changes in soil carbon pools resulting from land use change have received increasing attention. First, a species distribution model was employed to predict the potential distribution of Schrenk' s spruce forest on the northern slope of the Tianshan Mountains. Second, the area of Schrenk' s spruce forest converted to cropland (PSC) and the organic carbon loss caused by forest-to-cropland conversion were estimated. PSC was determined based on the actual distribution of Schrenk' s spruce forest, its potential distribution, and the actual distribution of cropland. Soil organic carbon contents in spruce forest land and cropland were obtained through field sampling and laboratory analysis. The study found that the PSC area was 2.68×10 hm^2, the soil organic carbon loss from Schrenk' s spruce forest converted to cropland was 171.7 t/hm^2, and the total organic carbon loss in the study area was 459.70 Tg. The results indicate that forest restoration and reconstruction projects in the study area will increase soil organic carbon storage, with greater increases in the surface soil layer than in deeper layers.

Full Text

Estimation of Soil Organic Carbon Loss from Picea schrenkiana Forest to Farmland in the Northern Tianshan Mountains

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Abstract: The impact of land-use change on soil carbon stocks has become an increasing concern in the context of global warming. This study first employed species distribution models to predict the potential distribution of Schrenk' s spruce (Picea schrenkiana) forests on the northern slope of the Tianshan Mountains. Second, we estimated the area of forest converted to farmland and the resulting soil organic carbon (SOC) loss. The area of potential Schrenk' s spruce forest cultivated to cropland (PSC) was determined by comparing the potential distribution of forests with the actual distribution of cropland. SOC content in forest and cropland soils was obtained through field sampling and laboratory analysis. We found that the PSC area was 2.68×10 hm^2, and the SOC loss per unit area caused by forest-to-cropland conversion was 171.7 t/hm^2. The total SOC loss in the study area was 459.70 Tg. Continuing afforestation and reforestation programs in the study area would increase SOC storage, with greater sequestration expected in upper soil layers than in deeper layers.

Keywords: Tianshan Mountains; Picea schrenkiana forest; potential distribution; land-use change; soil organic carbon loss

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Introduction

Over the past several decades, the relationship between greenhouse gas concentrations in the atmosphere and global warming has been a focal point of scientific research. Observational records from the Mauna Loa Observatory indicate that atmospheric carbon dioxide (CO), the most important greenhouse gas, has reached concentrations of 400 L/L—approximately 135% of pre-industrial levels (278 L/L) [1-2]. The Intergovernmental Panel on Climate Change (IPCC) reports that current atmospheric CO concentrations and associated radiative forcing are increasing at unprecedented rates, primarily due to anthropogenic land-use change and fossil fuel consumption [3]. Because forest soils store substantial amounts of organic carbon, researchers have conducted numerous studies on forest land-use/cover change (LUCC) and corresponding organic carbon losses across different forest ecosystems [5-7]. However, in the arid regions of northwestern China, research on carbon losses resulting from mountain forest conversion remains limited.

This study estimates carbon losses during land-cover change from Schrenk' s spruce forest to cropland on the northern slope of the Tianshan Mountains. The research focused on four main aspects: (1) classifying remote sensing images to obtain actual distributions of Schrenk' s spruce forest and cropland in the study area; (2) employing the Maximum Entropy model (MaxEnt) to predict the potential distribution of Schrenk' s spruce forest; (3) calculating the area of potential forest land that has been cultivated to cropland (PSC); and (4) estimating carbon losses associated with this land-use change using SOC content and density data.

The Tianshan Mountains, located north of the Tarim Basin and west of the Taklamakan Desert, were formed during the Cenozoic era by the collision of the Indian and Eurasian plates [8]. Vegetation types on the Tianshan Mountains vary with elevation, ranging from desert steppe and grassland forest belts at 1400–2800 m, to subalpine shrubland, to permanent snow and ice at higher elevations. The grassland forest belt is dominated by Schrenk' s spruce (Picea schrenkiana).

1. Study Area

[Figure 1: see original paper] Study area (northern slope of the Tianshan Mountains, blue-shaded regions)

2. Actual Distribution of Forest and Cropland

The actual distributions of Schrenk's spruce forest and cropland within the study area were derived from remote sensing image classification using the Classification and Regression Tree (CART) method in ENVI 4.8. Classification accuracy was evaluated using a kappa coefficient, which demonstrated the reliability of the classification results.

3. Potential Distribution Modeling for Schrenk' s Spruce Forest

The potential distribution of Schrenk's spruce forest was modeled using MaxEnt [9], a tool widely applied in forest restoration planning [10]. The model was trained using presence data from forest sample points, with located in China and in Kazakhstan and Kyrgyzstan. Chinese sample points were established through field surveys, while those in Kazakhstan and Kyrgyzstan were identified using Google Earth. To avoid overfitting, we selected eight predictive variables: mean annual temperature, minimum temperature of the coldest month, mean annual precipitation, precipitation of the wettest season, slope aspect, solar radiation, topographic wetness index (calculated from a Digital Elevation Model, DEM), and elevation [11-12].

MaxEnt was run with default settings: random test percentage = 25%; maximum background points = 10,000. We used 75% of sample points for training and 25% for validation. Model performance was assessed using the True Skill Statistic (TSS) rather than the Area Under the ROC Curve (AUC), as recent studies have questioned AUC' s reliability for presence-only data [15-16]. After obtaining the probability map of potential distribution, we converted probability values to binary presence/absence using a threshold selection strategy that maximized the sum of sensitivity and specificity [14].

The PSC area was calculated through spatial overlay analysis in ArcGIS using the formula: PSC = Pa   Ca, where Pa represents the actual distribution of Schrenk' s spruce forest and Ca represents the actual distribution of cropland.

4. Soil Sampling and Laboratory Analysis

During fieldwork, we collected soil samples from three parallel profiles at each sampling site in both forest and cropland areas. Samples were collected at 10-cm intervals from the surface to 80 cm depth or until bedrock was encountered. Soil organic carbon content was determined using the potassium dichromate volumetric method [17]. SOC density for each layer was calculated as:

$$soc_i = d_i \times c_i \times \delta_i$$

where soc_i is the SOC density (g/cm²) of layer i, d_i is the thickness (cm) of layer i (set to 10 cm in this study), c_i is the carbon content (g/kg) of layer i, and δ_i is the bulk density (g/cm³) of layer i. The total SOC density for the entire profile was obtained by summing values across all layers [18].

5. Carbon Loss Estimation

5.1 Actual and Potential Distribution of Schrenk's Spruce Forest The actual distribution of Schrenk's spruce forest was extracted from remote sensing classification results. MaxEnt modeling indicated that the potential distribution area of Schrenk's spruce forest on the northern slope of the Tianshan Mountains was 2.43×10 hm², with a TSS value of 0.753, demonstrating robust model performance. The actual forest area was 8.42×10 hm², representing only 28.81% of the potential distribution area.

[Figure 2: see original paper] Actual and potential distributions of P. schrenkiana forests

This study focused on potential forest areas that have been converted to cropland. Through spatial analysis, we calculated that 2.68×10 hm² of potential forest land has been cultivated, representing a significant land-use transformation.

5.2 Soil Organic Carbon in Forest and Cropland Laboratory analysis revealed distinct SOC density patterns between land uses. In Schrenk' s spruce forest, surface soil (0–10 cm) SOC density ranged from 4.25–13.79 kg/m² (42.5–137.9 t/hm²), with the highest values in the surface layer decreasing progressively with depth. At 70–80 cm depth, SOC density averaged 1.88 kg/m² (18.8 t/hm²). The total SOC density for the entire forest soil profile was 34.91 kg/m² (349.1 t/hm²).

SOC density of the soil profile of P. schrenkiana forest

In contrast, cropland soils showed lower SOC densities. The 0–10 cm layer averaged 3.07 kg/m^2, while 10–20 cm and 20–50 cm layers averaged 2.40 kg/m^2 and 2.74 kg/m^2, respectively. Notably, the decreasing trend did not continue in deeper layers; SOC densities at 50–60 cm and 60–70 cm increased to 3.33 kg/m^2 and 3.02 kg/m^2, respectively. The total SOC density for cropland soils was 17.74 kg/m^2 (177.4 t/hm^2).

[Figure 3: see original paper] General trend of SOC density along the soil profiles of cropland

5.3 Carbon Loss Calculation Based on these results, the total SOC density difference between forest (349.1 t/hm^2) and cropland (177.4 t/hm^2) was 171.7 t/hm^2, representing a 49.18% loss. When extrapolated across the entire PSC area of 2.68×10 hm^2, the total SOC loss amounted to 459.70 Tg.

It is important to note that these calculations represent the combined effects of natural factors and agricultural management practices. The soil samples were collected from actively managed farmland, and studies have shown that practices such as straw return, organic fertilizer application, increased chemical fertilizer input with balanced nutrient ratios, and reduced tillage can increase SOC in croplands [19]. Therefore, the difference in total SOC density between forest and farmland calculated in this study may be smaller than under natural conditions, and the actual carbon loss could be lower.

6. Discussion

Due to various environmental and anthropogenic factors, quantifying SOC loss after cultivation is challenging. Niu and Duiker [20] estimated carbon loss by delineating potential forest land on marginal agricultural land, using land-cover datasets and soil geographic databases. However, this approach does not clarify whether the designated forest land is biologically and climatically suitable for forest growth. Schulz et al. [21] combined the Dyna-CLUE land-use change model with a carbon bookkeeping model to predict future land use and associated carbon losses across Europe, highlighting the complexity of integrating models at different scales and the uncertainties inherent in land-use scenario predictions.

[Figure 4: see original paper] Difference in SOC density between forest and cropland soils

This study estimated carbon losses on the northern slope of the Tianshan Mountains through field surveys, laboratory analysis, and modeling, requiring relatively few data types compared to process-based models. However, model uncertainty remains a concern. Don et al. [22] found that the greatest carbon losses occur when primary forests are converted to cropland (-25%) and perennial crops (-30%). Our results suggest that if farmland were restored to natural forest, carbon stocks could increase substantially. Because SOC increases can occur in each soil layer, examining differences in SOC accumulation across soil layers enhances understanding of carbon dynamics following land-use change.

This study confirms the well-documented trend of decreasing SOC with soil depth in forest soils [23] and further reveals that differences in SOC content between forest and cropland are greater in upper soil layers than in deeper layers. Consequently, upper soil layers may contribute more to carbon sequestration gains from reforestation and forest restoration programs.

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Note: Figure translations are in progress. See original paper for figures.