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An assessment of collective action drivers of carbon storage in Nepalese forest commons

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ABSTRACT

Decentralized forestry has evolved as a strategy for the management of forests in many developing countries and key institutional factors driving forest collective action have also been identified. We analyzed 130 Nepalese forest commons to determine how key forest collective action variables are associated with carbon storage. As expected, we find household participation in forest management and public audit have favorable implications for carbon storage. However, we also find conservation duration, communities' ability to modify rules and existence of penalty system have constraining, and mutual trust have no or neutral implications for carbon storage. These findings indicate that better collective action does not necessarily store additional carbon. If forest commons in developing countries are to contribute to global climate change initiatives, such as the United Nation's program on Reducing Emissions from Deforestation and Forest Degradation (REDD +), our findings suggest the need for dedicated policies and programs to create additional incentives.

1. Introduction

Approximately 15.5% of global forests and 25% of developing country forests are under the control of local communities (“forest commons”) and this trend is increasing (Rights and Resources Initiatives [RRI], 2014; Kumar, 2002). A key reason for this trend is that governments in many developing countries have been devolving and decentralizing forest control with the aim to stop deforestation, manage forests sustainably and increase provision of forest products to communities (Larson and Soto, 2008; Persha et al., 2011). Given their importance, forests controlled by communities are also potentially critical for contributing to climate change mitigation through carbon storage, particularly with the emergence of the United Nation's program on Reducing Emissions from Deforestation and Forest Degradation (REDD +) as a cost-effective strategy to reduce emissions (Kinderman et al., 2008). Karky and Skutsch (2010) estimates that the opportunity cost of carbon sequestration in community forests in Nepal may be less than $1.00 per ton, but more recent literature calls these very low Nepal estimates into question (Maraseni et al., 2014; Pandit et al., 2017).

Effective management of forest commons relies heavily on collective action, which depends on trust and reciprocity among community members, who adopt norms while pursuing contingent strategies in complex and uncertain environments (Ostrom, 1990). Norms are critical to resolving social dilemmas via building and maintaining community self-organization, trust and reciprocity. Ostrom (1990) identified norms guiding collective action, which she articulated in terms of institutional design principles that can vary significantly across contexts (Cox et al., 2010). Such norm guiding collective action has been evident in effective management of forest resources in developing countries. For example, in Nepal forest collective action has contributed to reducing deforestation and forest degradation and restoring degraded forests (Department of Forest Research and Survey [DFRS], 2015; Gautam et al., 2002), but communities' harvesting, grazing and burning in some cases have also resulted in loss of forest carbon (Flint and Richards, 1994; Food and Agriculture Organization [FAO], 1993; Goldammer, 1990).

Agrawal and Angelsen (2009) highlight the need to strengthen collective action that increases both carbon storage and livelihood outcomes. However, there remains large uncertainty whether and when forest commons sequester more carbon (Chazdon, 2008; Ranganathan et al., 2008; Beyene et al., 2015), making it difficult to know to what extent programs such as REDD + need to provide specific and direct incentives for carbon sequestration.

Using worldwide forest data and highly aggregated forest collective action elements, Chhatre and Agrawal (2009) demonstrate there are possibilities for both tradeoffs and synergies between carbon sequestration and livelihoods of communities. They conclude by suggesting the need for detailed studies to better understand the implications of REDD + when forests are controlled by communities. Similarly, in the Amazon, Bottazoi et al. (2014) recommend that focusing

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simultaneously on the intersection of institutional, socio-economic and biophysical factors is needed to better understand the implications of REDD +. In addition, Beyene et al. (2015) evaluate the effect of local community forestry collective action on carbon sequestration in Ethiopia, but find minor effects. Yadav et al. (2003), Gautam et al. (2003) and others claim that CFs in Nepal can help reduce forest degradation, which could imply less carbon emissions that should be credited under REDD +.

Nepal has a long history of community-based indigenous, traditional forest management practice. Building on such management practice, it has developed and adopted different models of community-based forest management such as community forestry, leasehold forestry, and government-managed forestry. It is one of the pioneer countries in creating legally supported forest commons over the last 40 years. Approximately 42% of the population are formally organized in ~19,000 Community Forest User Groups (CFUGs), which are engaged in managing ~1.8 million hectares of forests (Department of Forest, 2015). The CFUGs are autonomous public bodies that can acquire, possess, transfer and manage forests (Ministry of Law and Justice [MoLJ], 1993).

Using multivariate regression analysis and data from a sample of 130 forest commons and 1300 households across Nepal, we examine the relationship between key collective action drivers and carbon storage, while controlling for the effects of major conditioning variables, such as location, topography, quality and quantity of forests and population structures. Specifically, we consider communities' forest conservation histories, governance practices, monitoring and sanctioning, and social capital, as they constitute critical common property design principles (Cox et al., 2010; Ostrom, 1990).

2. Methods

2.1. Sampling and data collection

From February to May 2013 we collected data from 130 forest commons, 65 formal community forests (CF) and 65 non-community forests or non-CFs (NCFs), distributed in 42 districts across different physiographic regions (Fig. 1). As CFs are owned and actively managed by local communities and NCFs are owned and loosely managed by the government, but traditionally used by local communities, these categories make up the major types of forest commons in Nepal (Fig. 1).

Our interest in this paper is not to compare the results across CFs and NCFs, but to instead identify relationships between carbon stock and key collective action drivers, with less emphasis on management. We randomly selected CFs from a nationwide random sample used to evaluate the impact of the Nepal Community Forestry Program by the Nepalese government in 2010–12 (MoFSC, 2013). In related work (e.g. Bluffstone et al., 2018) that required comparability between CF and NCF observations, we selected NCFs in consultation with district forest office members. Such forests were not next to CFs to avoid being used simultaneously by the same communities.

We estimated that a sample of 325 forest plots was required for our study in the CFs to provide a nationally representative sample for Above-Ground Tree and Sapling Carbon ("carbon") estimation. This sample size was calculated based on a pilot survey of 45 forest plots (nine CFs) across physiographic regions that captured the greatest possible variance in the plot-wise carbon and applying Eq. (1) for a 10% error and 95% confidence level (Saxena and Singh, 1987).

$$N = C_v{}^2 t^2 / E^2 \tag{1}$$

where,

N = Required number of sample plots;

C_v = Coefficient of variation, s/μ (s = standard deviation and μ = sample mean);

E = Standard error, $s/\sqrt{n}$ (n = sample number);

t = Value of student-t distribution for $(n - 1)$ degree of freedom and 95% confidence level.

We sample 3 to 7 plots in each of the 65 CFs. We determined the number of plots in a forest according to the quintile distribution of forest size. These quintiles are computed separately for the hills and the southern plain lands (Terai) as average size of forests in the Terai is substantially greater than the hills (Table 1). The 65 NCFs are government forests that are used by the local communities and are often open access. Using the same criteria and methods as for the CFs, we selected 295 NCF plots in the 65 forests.[1]

To collect data on trees and saplings in each plot, we randomly selected concentric circular plots with radiuses of 8.92 m and 5.64 m to, respectively, which are suitable for moderate to dense vegetation and have been widely used (MacDicken, 1997). We identified the species and measured height and diameter at breast height (DBH) of each tree and DBH of each sapling.

We also randomly selected 10 households from each CFUG to complete questionnaires used to collect socio-economic data. We tested the questionnaires in two CFUGs and six households for their appropriateness and finalized them before conducting the full survey. We selected, trained and deployed 25 field researchers having either forestry or social science backgrounds. We closely and constantly monitored data collectors and supported them to ensure effectiveness of data collection and quality of data.

2.2. Analytical framework: variables, hypotheses and model specifications

We use multivariate regression to assess the relationships between collective action drivers and carbon storage by constructing a two-stage model. First, we estimate the carbon for each forest. Second, we construct a regression model with carbon as the continuous dependent variable and collective action drivers as the explanatory variables. We include critical conditioning variables in our model to mitigate potential biases due to omitted variables.

2.2.1. Variable selection and hypotheses setting

We carefully selected dependent, explanatory and conditioning variables (Table 2). We transformed all tree and plot data to the forest level (e.g., Mg C ha^{-1}) by averaging, and all household data to the community level so as to match the level of data for further analysis.[2]

2.2.1.1. Dependent variable. Our dependent variable is aboveground live carbon (Mg C ha^{-1}). We use Eqs. (1) and (2) to estimate Above-Ground Biomass (AGB). These allometric equations were developed based on a large dataset of trees across different climatic conditions of global sites, in dry (< 1500 mm average annual rainfall) and moist (1500–4000 mm average annual rainfall) forests, respectively (Chave et al., 2005) and recommended for Nepal by the Nepalese Government (Ministry of Forest and Soil Conservation [MoFSC], 2010). Approximately 95% and 5% of our samples are in moist and dry forests, respectively.

$$\text{AGB (kg)} = 0.112^*(\rho^*\, D^2H)^{0.916} \tag{1}$$

$$\text{AGB (kg)} = 0.0509^*\, \rho^*\, D^2H \tag{2}$$

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[1] 30 plots had to be dropped due to data collection problems.

[2] For carbon, we converted the size-wise plot estimates (for trees 250 m^2 plot and for saplings 100 m^2 plot) to per hectare by multiplying by appropriate factors (e.g., by 40 for trees plots and by 100 for sapling plot). Then per hectare carbon of tree and sapling were added to get the total carbon per hectare at the plot level. Then by taking an average of plot level carbon (Mg C ha^{-1}), we estimated the forest level carbon (Mg C ha^{-1}). Similarly, other data collected at the plot level were averaged to estimate forest level data (e.g., slope, altitude and NDVI). Other data collected at the household level were aggregated to the community level. As community is the decision-making level for collective action and forest management, analysis at the community level is appropriate.