



## STUDY ON INTERNAL TIMBER DEMAND SUPPLY RATIO IN COMMUNITY FOREST

### USERS' GROUPS OF MIDDLE MOUNTAIN REGION OF NEPAL

Bishwa Bandhu Sapkota<sup>1\*</sup>, Kisman Bhattarai<sup>2</sup> and Simant Rimal<sup>3</sup>

<sup>1</sup>School of Forestry and Natural Resources, University of Arkansas at Monticello, USA

<sup>2</sup>Institute of Forestry, Hetauda Campus, Tribhuvan University, Hetauda, Nepal

<sup>3</sup>Agriculture and Forestry University, Hetauda, Nepal

\*Corresponding author: bishowbs08@gmail.com

#### Abstract

Higher internal timber demand compared to the supply capacity of forest has been attributing to scarcity of timber within Community Forest Users' Groups (CFUGs) and subsequently posing risk to the sustainability of forest. It is therefore becoming crucial to examine the factors behind such high demand to supply ratio and quantify their relationship to help in optimum allocation of forest resources to the community. In this study, we selected potential variables that could affect the internal demand-supply (DS) ratio in a community forest users' groups, examined their correlation with it, and develop a parsimonious model that could explain the relationship between them using linear regression technique and Akaike Information Criterion methodology. The correlation coefficient analysis showed that household density (0.75) had very strong relationship whereas other predictor variables such as, growing stock per hectare (0.35), percentage of households involved in agriculture (0.37), area of forest (-0.39), percentage of timber yielding species in a forest (-0.56), and percentage of rich household (0.62) in a CFUG had weak to fair relationship with DS ratio. Among the four different models designed with the top three highly correlating variables, the third model utilizing household density and percentage of timber yielding species proved to be most parsimonious model. The developed linear model is of high relevance for forest officials in rational and scientific formation of community forest users' group and handover of forest resources to such groups.

Keywords: Operational plan, Sustainability, Linear regression modeling, Akaike Information Criterion, Timber demand-supply, Community Forest.

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## **Introduction**

Community based forest management is one of the most successful forest management approaches at present context in Nepal (Aryal et al., 2013). Nepal has been adopting this approach as one of the prominent management strategies since late 1980s, that could better manage forest on one hand and uplift the livelihood of local people on the other hand (Pokhrel and Nurse, 2004; K.C et al., 2014). In this modality, community forest users' group (CFUG), a group of people who are willing to manage accessible forest on their own, are formed through broad participatory stakeholder analysis and the group is finally registered officially in District Forest Office. Before they could start managing and procuring benefits from community forest, they are mandated to prepare forest operational plan and constitution (MoFSC, 2000).

Community based modality has been proving successful in terms of its achievement in poverty alleviation, resources mobilization, institutional set up and development, social integrity enhancement, common property resource conflict resolution etc. (Ojha et al., 2009). It is designed at its best to propagate from subsistence to commercialization of timber ends and to deliver more economic security to local community. Despite its several merits, some problems still exist at CFUG level at present context in Nepal. Unscientific allocation of forest resources as community forest by government bodies and non-governmental organizations without extensive study of dimension and structure of user group and forest resources is indirectly impacting on the balance between demand and supply of timber within a CFUG. As a consequence, sustainability of community forest is being compromised and productivity of forest is affected (Kanel et al., 2012). Therefore, a thorough study of different causative factors and their level of inter-correlation with demand-supply ratio is required for understanding the problem at root level, which in turn is required for formal endorsement of the problem and subsequently the policy revision.

As of 2017, Middle mountain region of Nepal harbors a total of 13,808 CFUGs covering an area of 1,162,661 ha that supports 1,514,676 households directly (CFD, 2017). In case of Middle Mountain, the demand for timber was found to be 1.72 million m<sup>3</sup> in the year 2011 and it is projected to rise to 2.33 million m<sup>3</sup> in the year 2030. Similarly, the supply of timber from CF in mid hills was 0.71 million m<sup>3</sup> and it is projected to rise to 1.6 million m<sup>3</sup> by 2030 (Kanel et al., 2012). Our preliminary study on operational plans and constitutions of 200 CFUGs also shows that internal timber demand exceeds allowable timber

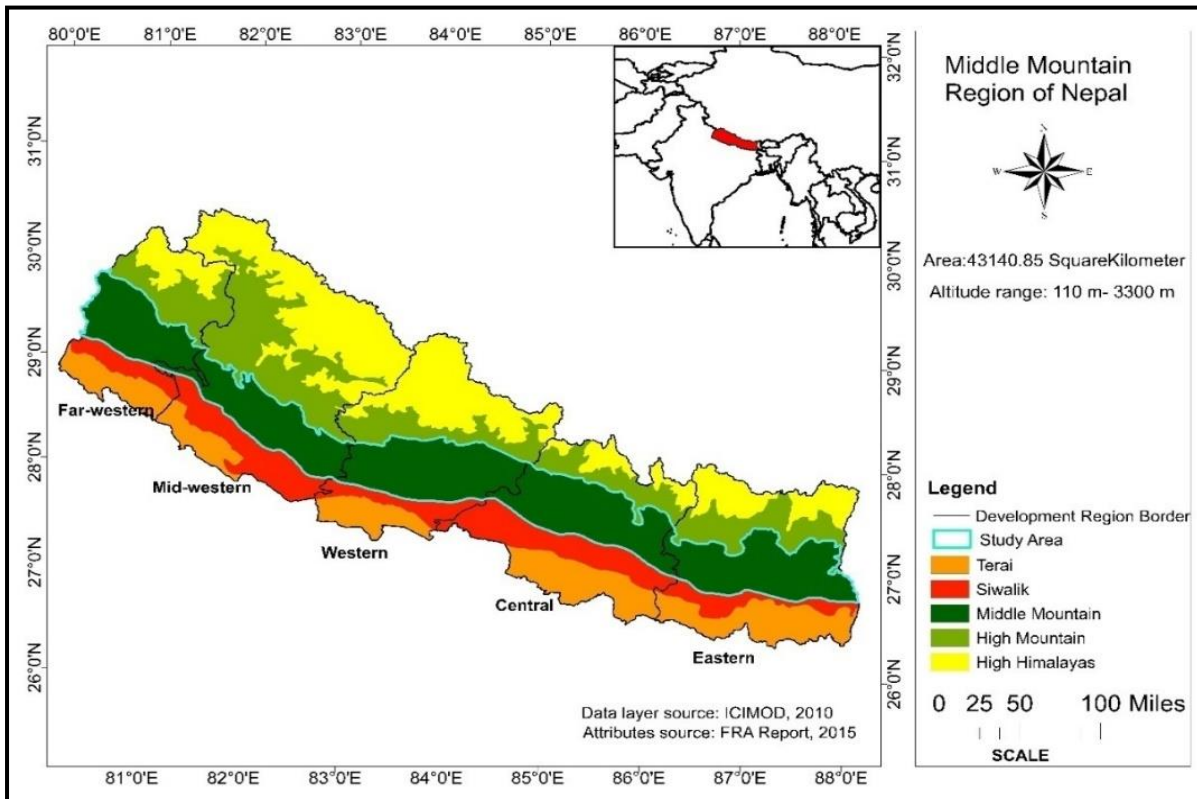
cut in majority (190 out of 200) of CFUGS. Therefore, the gap between demand and supply is becoming a matter of concern these days (Lamichhane, 2009) and has raised questions over currently practiced methodologies and policies regarding timber harvest from community forests. Especially, this problem is of great concern in middle mountain region where around 60% of total number of CFs in Nepal are distributed (DFRS, 2015).

The objectives of the study were two folds: (a) Assessing the degree of correlation of different predictor variables with internal timber Demand-Supply(DS) ratio and (b) Deriving the most parsimonious model to explain relationship between internal timber DS ratio and associated determinants.

## **Materials and Methods**

### ***Study area description***

Our study area is middle mountain region ( 26°40' to 29°38' N latitude and 80°01' to 88°10' E longitude), the largest physiographic region and the most populated region of the country with approximately 10.45 million people, which comes to be around 41% of the total population of the country. Average population density is about 550 individuals per square kilometer and the average household size is 4.81 individuals (DFRS, 2015). The region has altitudinal range of 110 to 3300 m. The climate ranges from sub-tropical in river valleys like Koshi, Gandaki, Kamali, and Mahakali to cool-temperate in high hills. The average annual maximum temperature is about 23.5<sup>0</sup>C, and the average annual minimum temperature is about 12.7<sup>0</sup>C. Annual precipitation varies from east to west with highest in Western Development Region (1,898mm) and lowest in Central Development Region (1,091mm). Both sub-tropical mixed evergreen forest (elevation: 1000-2400m) and temperate evergreen forest (elevation: 2400m-3600m) are found in this area. Major timber species like *Schima wallichii* and *Castonopsis indica* are found at lower altitudes. Upper portion of middle mountain region comprises non-timber species like spruce, deodar, cedar etc. (DFRS, 2015).



**Figure 1.** Map showing study area (Middle mountain region).

### *Data collection*

The study was conducted using secondary data. Operational plan and constitution of CFUGs which were prepared or revised within timeframe of 2014-2017 were used as source of information for predictor and response variables. Altogether 120 CFUGs with good database of OP and constitution were chosen as samples ensuring more or less uniform coverage across different development regions within middle mountain region. Out of 120 samples, 80 samples were randomly selected to train various models and remaining 40 samples were separated as holdout test sample for model validation purpose. The sample size was determined taking into account the time and budget factor and availability of every required data in operational plan and constitution.

**Table 1.** Description of predictor variables selected for study. CFUG: Community Forest Users' Group

S.N	Predictor variables	Description	Data source	Assigned Code
1	Average growing stock per hectare	Total growing stock (trees and pole) in cubic feet divided by area of forest	Operational plan	G
2	Area of forest	Area of the community forest (in Hectares) delineated and explained in Constitution	Operational plan	A
3	Percentage of timber yielding species in forest <sup>1</sup>	Timber yielding species per hectare divided by total number of tree species per hectare	Operational plan	TY
4	Household density	Total number of households in a CFUG divided by total area of the community forest in hectare	Operational plan	HH
5	Percentage of Households involved in agriculture	Total number of households with agriculture as main occupation divided by total number of households in a CFUG.	Constitution	AH
6	Percentage of rich household <sup>2</sup>	Total number of rich households divided by total number of household in a CFUG.	Constitution	RH

<sup>1</sup> The percentage observed in every inventory plots in operational plan were totaled and averaged to achieve an average percentage of timber yielding species in a forest.

<sup>2</sup> The households ranked A and B in well-being ranking (A-D) survey form attached in each CFUG constitution were categorized as rich household.

Six independent variables relating to demand and supply of timber within CFUG were chosen as predictor variables based on expertise knowledge, on-field experience and general understanding (Table 1) Internal timber DS ratio, which is the response variable, was calculated as the ratio of total demand of timber made by users in a CFUG to total allowable timber harvest as stated in operational plan of CFUG.

### *Data analysis*

Pearson correlation coefficient ( $r$ ) (Pearson, 1895) was calculated to determine the degree of correlation of predictor variables with response variable i.e. DS ratio. The degree of correlation of predictor variables was categorized into five categories namely very strong, strong, fair, weak, and very weak or no relationships based on thumb rule given by Salkind (2016). Only the top three highly correlating variables were used in designing candidate models using multiple linear regression modelling technique, one of widely used statistical tools that graphs the relationship between two or more than two different causative factors and the effect (Kutner et al., 2000). Other variables were neglected because accounting weak correlating variables would instead over fit the model.

Akaike Information Criterion (AIC) methodology was also employed to choose the most parsimonious one among the designed models. The formula to calculate AIC score given by Akaike (1981) is expressed as below:

$$AIC = 2K - 2 \log(L) \quad (1)$$

Where,  $K$  is the number of independent variables used and  $L$  is log-likelihood at maximum point of model estimated. For small data samples, above formula is revised as:

$$AIC_c = AIC + \frac{2K(K+1)}{n-K-1} \quad (2)$$

Where  $AIC_c$  is corrected Akaike score and  $n$  is number of sample size

AIC methodology requires the calculation of other statistics, difference in  $AIC_c$  score of individual model and the lowest  $AIC_c$  score ( $\Delta AIC_c$ ), and Akaike weightage for individual models ( $w_i$ );

$$\Delta AIC_c = AIC_c(i) - AIC_c(m) \quad (3)$$

$$w_i = \frac{\exp(-0.5 \times \Delta AIC_{c,i})}{\sum_{r=1}^R \exp(-0.5 \times \Delta AIC_{c,i})} \quad (4)$$

Where,  $AIC_c(i)$  is the individual  $AIC_c$  score for each model and  $AIC_c(m)$  is the minimum  $AIC_c$  score of the model tested;  $R$  is the number of models, and  $r$  is the model being accounted.

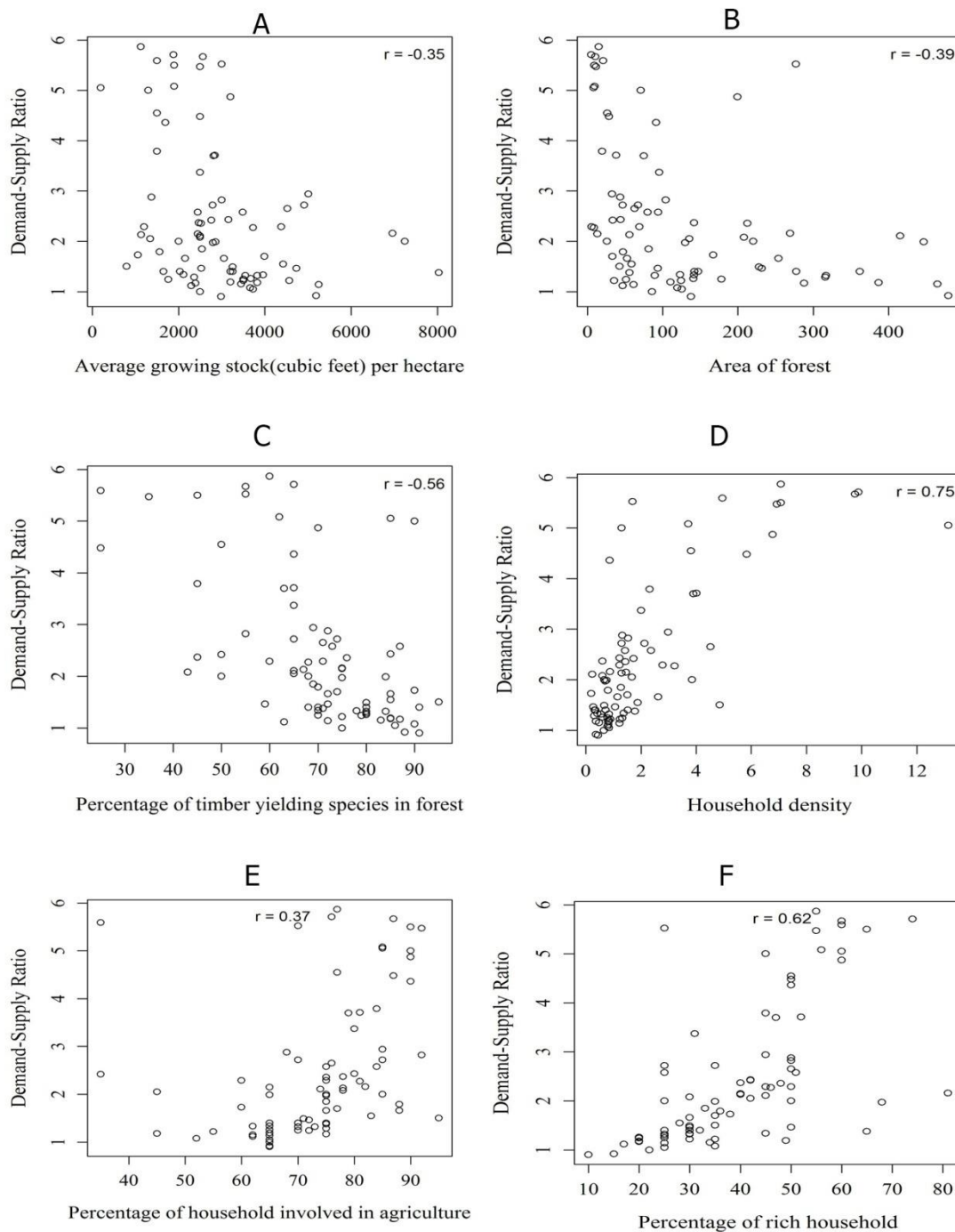
Finally, hold-out test samples were used for assessing the fit of the parsimonious model. Residual standard error and adjusted R-squared value was calculated to assess how exactly the parsimonious

model fitted to the observed data. Residual error plot and histograms were also produced to manifest the distribution of residuals across the predicted values.

## **Results and Discussions**

### ***Correlation analysis***

The correlation coefficient for growing stock per hectare, household density, percentage of rich households, percentage of households involved in agriculture, percentage of timber yielding species in forest, and area of forest were -0.35, 0.75, 0.62, 0.37, -0.56, and -0.39 respectively (Figure 2). Household density had highest correlation coefficient whereas growing stock per hectare had the lowest. Percentage of households involved in agriculture and area of forest showed weak correlation whereas other remaining variables i.e. percentage of timber yielding species in forest and percentage of rich household showed fair correlation with the response variable. It is pretty sensible and reasonable to find household density as having highest degree of correlation among other predictor variables for the fact that household density accounts the combined effect of both number of households in a CFUG and area of the forest. For example, for a given 1 ha of forest area, more the users to utilize the resources, the more is the demand for timber in relation to constant timber supply capacity of the forest. Since, harvesting guidelines permit the user group to harvest only the trees, the growing stock of forest, which is a sum of growing stock of trees and poles, may not be an indicative of timber supply from a community forest. For example, a community forest with higher average growing stock may have low proportion of growing stock of trees but more proportion of pole and thus may hold lower capacity for timber supply.



**Figure 2.** Scatterplots showing correlation of different predictor variables with demand-supply ratio. A) Average growing stock (cubic feet) per hectare, B) Area of Forest (Hectare), C) Percentage of timber yielding species in forest, D) Household density, E) Percentage of household involved mainly in agriculture in a Community Forest Users' Group, and F) Percentage of rich household in a Community Forest Users' Group.



### *Design of linear models and selection of the most parsimonious model*

Following four models were proposed with various combinations of predictor variables such that household density variable was kept in every model as it had the highest coefficient of determination.

$$M1: DS \text{ ratio} = \beta_0 + \beta_1 HH \quad (5)$$

$$M2: DS \text{ ratio} = \beta_0 + \beta_1 HH + \beta_2 RH \quad (6)$$

$$M3: DS \text{ ratio} = \beta_0 + \beta_1 HH + \beta_2 TY \quad (7)$$

$$M4: DS \text{ ratio} = \beta_0 + \beta_1 HH + \beta_2 RH + \beta_3 TY \quad (8)$$

Where  $\beta_0$  is the intercept value for each model and  $\beta_1, \beta_2$ , and  $\beta_3$  are slope for each predictor variables in the model; HH, TY, RH represents household density, percentage of timber yielding species, and percentage of rich household. M1, M2, M3, M4 represent model 1, model 2, model 3, and model 4 respectively.

Model statistics in Table 2 shows that model 1 had the highest standard residual error (1.99) whereas model 3 had the lowest (1.77). Adjusted R-square value was lowest for model 1 (0.61) and highest for model 3 (0.7). Looking into standard error and adjusted R- square statistics in Table 2, model 3 was determined to be the desired model among all. AIC statistics were also computed in order to determine the most parsimonious model.

AIC statistics in Table 3 shows that AICc score was highest for model 1 (333.31) and lowest for model 3 (316.04).  $\Delta AICc$  was lowest for model 3 (0) and highest for model 1 (17.27) whereas Akaike weightage ( $w_i$ ) was highest for model 3 (0.74) and lowest for model 1 (0.00013). Since, the model with lowest  $\Delta AICc$  is said to be the most parsimonious (Akaike, 1981), model 3 was determined as the most parsimonious model among four models. This conclusion was consistent to the claim made based on model statistics given in Table 2. Therefore, Equation 9 was determined to be the model that would best explain the relationship between DS ratio and its predictor variables.

$$DS \text{ ratio} = 5.92 + 0.8 * HH - 0.069 * TY \quad (9)$$

Where DS ratio, HH, and TY represent Demand-Supply ratio, Household density, and Percentage of timber yielding species in a community forest respectively.

**Table 2.** Model statistics.

Model		Estimate	Standard Error	Pr(> t )	Standard Residual Error	Adjusted R-Square
1	$\beta_0$	0.75	0.29	0.0125 *	1.99	0.61
	$\beta_1$	0.94	0.083	$<2e-16^{***}$		
2	$\beta_0$	-0.72	0.8	0.36	1.95	0.63
	$\beta_1$	0.75	0.12	$4.2e-08^{***}$		
	$\beta_2$	0.05	0.02	0.05		
3	$\beta_0$	5.92	1.14	$2.02e-16^{***}$	1.77	0.7
	$\beta_1$	0.8	0.08	$2.22e-15^{***}$		
	$\beta_2$	-0.069	0.01	$1.60e-05^{***}$		
4	$\beta_0$	5.490632	1.700456	$1.8e-04^{**}$	1.78	0.69
	$\beta_1$	0.772757	0.112954	$1.94e-09^{***}$		
	$\beta_2$	0.008585	0.024821	0.73		
	$\beta_3$	-0.066892	0.016507	$1.24e-04^{***}$		

Note: \*\*\*, \*\*, \* represents significance at 0.001, 0.01, 0.05 level of significance respectively.

$\beta_0$  represents intercept for each model and  $\beta_1, \beta_2, \beta_3$  represents slope for each parameters in the model as shown in Equation 5 - 8.

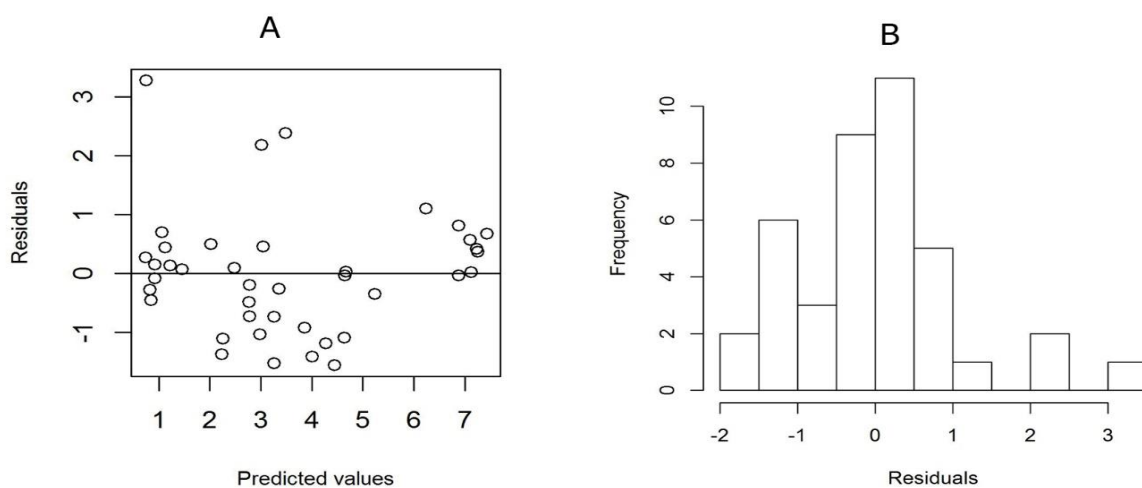
**Table 3.** Summary of Akaike Information Criterion (AIC) for different models. AICc - Akaike Information Criterion corrected,  $\Delta AICc$ - Difference of AICc score for current model and the model with least AICc score,  $w_i$  - Akaike weightage for a model (See Equation 3 and 4 for  $\Delta AICc$  and  $w_i$  respectively).

Model	AIC	AICc	$\Delta AICc$	$w_i$
1	333.27	333.31	17.27	0.000133
2	331.51	331.55	15.51	0.00032
3	316	316.04	0	0.746156
4	318.16	318.2	2.16	0.253391

It is quite surprising to find model 3 with higher adjusted R-square than the model 2 despite the fact that model 2 utilized the top two highest correlating variables - Household density and Percentage of rich household (Figure 2). The reason could be attributed to the collinearity between these two variables. It is found that inter-correlations can yield less precise estimates, can induce parameters to switch signs, and affect R-squared value (Mela and Kopalle, 2002).

### ***Validation of selected model***

Predicted data showed fair correlation with observed data (adjusted R-squared: 0.52, residual standard error: 1.04). Likewise, Figure 3 (A) and Figure 3 (B) shows that more than 60% of predicted data had residual error between -1 to 1, which corroborates a fair fit of the model to the observed data.



**Figure 3.** Residual error plot graph (A) and Histogram showing the frequency of residuals (B)

The results of correlation analysis indicate that higher household density results in higher demand-supply ratio of timber in the community forest. This is in agreement to the findings by Rai et al. (2016) that size of the benefits from CF depend upon the number of households collecting woods. Similarly, our results also reveals that CFUGs with more number of rich households has more DS ratio. The study by Baral et al. (2009) also discusses the positive relationship of number rich households with the demand of timber in the CFUG. According to the study, richer users are involved in larger scale of agriculture and usually are in need of more timber. Similarly, Adhikari and Lovett (2006) also mentions that better off households demands for more forest product, increasing finally the transaction costs. Density of timber yielding species is also found to significantly affect DS ratio in our study. Lammichhane (2009) analyzed the

consumption pattern of fuel wood and timber in community forests in Sindhupalchowk district and found that pine-dominant community forest had more supply capacity than any other community forest. The variables such as, area of forest and growing stock didn't show strong relationship with timber demand and supply as opposed to what was expected. The reason could be attributed to low density of harvestable tree species in a large forest.

The issue raised in this study had also been emphasized in other studies. Kanel et al. (2012) studied the demand and supply of wood products in different regions of Nepal and projected statistics of demand supply in future. They emphasized on the effects of prevailing paradigm of timber harvest in CFUGs on internal timber DS ratio and suggested for optimum allocation of forest resources to the community and other administrative reforms to cope up with this emerging timber deficit problem.

The model selection procedure used in this study i.e. Akaike Information Criterion has been used successfully in several other studies for selecting the best model. Mazerolle (2006) used AIC in herpetological datasets to select the parsimonious model that could be routinely adopted by herpetologists. Likewise, Snipes and Tylor (2014) determined the model that described the factors that affect the rating of wine using AIC methodology. This methodology avoids multiple testing issues and is valid for both nested and non-nested models. However, it should be remembered that AIC cannot be used to compare models on different datasets.

## **Conclusions**

In conclusion, this study developed a linear model that could explain the relationship between internal timber demand-supply ratio and its potential predictor variables and explained the nature and degree of correlation between them. The findings and the model developed in this study can be of great importance when it comes to scientific formation and handover of CFUGs, development of benefit sharing mechanism within CFUGs, and quantification of timber DS ratio throughout middle mountain region. An extensive post-simulation of the model can yield optimum suitable household density which can be very useful during allocation of forest resources to CFUGs. Although the findings were very encouraging, the study had some limitations, which are listed below.

- ❖ Other predictor variables such as regeneration capacity, geographic status of forest, percentage of households with wooden houses and timber enterprises, etc., which may directly or indirectly

correlate to DS ratio, were not accounted because not every operation plan and constitution had data for these variables.

- ❖ The suitability and possibility of other non-linear relationships for this study was ignored.
- ❖ The data for demand was based on response by users on question that how much timber they would need in a year instead of actual demand figures based on prevalent timber consumption rate within.

Overcoming these limitations might result in more accurate depiction of relationship between internal timber demand-supply ratio and its predictor variables.

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