Forest reliance across poverty groups in Tanzania

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Abstract

An emerging body of knowledge has established that poorer households in forest adjacent communities in developing countries are generally more forest reliant (higher forest income share) while richer households tend to extract more and generate higher absolute forest income. These studies commonly categorize households based on observed income in cross-section data, presenting a snap-shot reflecting both inter-household and inter-annual income variation. In this paper we introduce a new approach to categorize households based on a combination of the observed one-year income and predicted income by an augmented asset approach. Applying this approach on household data from Tanzania, we find forest reliance to be high among structurally poor households (low observed income and assets). The highest forest reliance is, however, found among the stochastically non-poor households (high observed income and low assets), and this group also has the highest absolute forest income.

Keywords: Forest dependence; poverty categories; asset poverty; cross-sectional data

Highlights:

- Stochastically non-poor (high income, low asset) has the highest forest reliance
- Stochastically non-poor also has the highest absolute forest income
- Structurall*y* non-poor (high income, high asset) do *not* use more forest products
- Using *predicted* income yields new insights on the poverty and forest reliance nexus
- The new method to categorize households should complement conventional categorizations

1 Introduction

Quantifying the contribution of forest income in rural economies in developing countries is important to understand the welfare implications of deforestation and forest degradation and to design effective development and conservation strategies (Cavendish, 2002; Angelsen and Wunder, 2003; Vedeld et al., 2004; Angelsen et al., 2014). We can distinguish between three potential functions of forest income in rural livelihoods (Angelsen and Wunder, 2003; Cavendish, 2002). First, forest income supports current consumption and subsistence needs in terms of providing sources of energy, nutrition, construction material and medicinal plants. Second, forest income can serve as a safety net to overcome an unexpected income loss or high expenditure. Third, forest incomes may provide a pathway out of poverty by providing regular cash income. Forest income include cash and subsistence incomes from products harvested in forested areas, such as firewood, timber, and non-timber forest products (NTFPs).

In a global-comparative analysis of environmental income in 58 sites in 24 developing countries, Angelsen et al. (2014) find that forest income on average account for 22% of total household income. This figure is similar to that reported in an earlier meta-analysis of 51 case studies (Vedeld et al., 2007). A well-established pattern is that the poorer households obtain a higher share of their total income from the forest while richer households extract more forest resources and generate a higher absolute value of forest income (Cavendish, 2000; Adhikari et al., 2004; Fisher, 2004; Mamo et al., 2007; Vedeld et al., 2007; Babulo et al., 2009; Kamanga et al., 2009; Nielsen et al., 2012; Rayamajhi et al., 2012; Angelsen et al., 2014). Further, many studies find that forest income mainly support current consumption., such as the study by Kamanga et al. (2009) in Malawi, Nielsen et al. (2012) in the Democratic Republic of Congo, Heubach et al. (2011) in Benin and by Rayamajhi et al. (2012) in Nepal.

These studies also recognize that forest income may serve as a safety net in case of a negative income shock. This is supported by Debela et al. (2012) in their study from Uganda, where large shocks were associated with a higher use of forest resources in subsequent periods, particularly among the asset poor households. However, Wunder et al. (2014) question the universality of the forest safety net function. Although some households are able to accumulate cash from forest use, the role of forest income as a pathway out of poverty is even more contested (Angelsen and Wunder, 2003). This partly reflects the subsistence nature of most forest uses, and that if profitable opportunities exist they tend to be captured by elites (Dove, 1993). But positive case studies exist;

Shackleton et al. (2007) finds that forest products offer a pathway out of poverty for some households in South Africa. (Ainembabazi et al., 2013) reported similar findings for charcoal in Western Uganda and Duchelle et al. (2014) for Amazon (Brazil) nut in Northern Bolivia.

Most forest-poverty studies use observed one-year income from cross-sectional data to categorize households into poverty groups. Typically, they do not take into account that incomes fluctuate greatly from year to year and therefore provide a static analysis of the forest-poverty nexus. The conventional approach therefore fail to distinguish between inter-household and inter-annual income variation. Panel data studies have found that households that are categorized as poor in one period may not be poor in the next period (and vice versa) due to random fluctuations in crop yields and prices, and irregular earnings from casual labor, remittances etc. (Carter and Barrett, 2006). Similarly, some of the households with high observed income might have been lucky in one survey year, but will again be among the low-income households next year. In a study from Ethiopia, Dercon and Krishnan (2000) found that one third of the households identified as poor in the first year in a two-year panel data set were different from the households identified as poor the second year. The snapshot provided by cross-sectional data might therefore be misleading.

Carter and May (2001), among others, have highlighted the importance of assets in poverty analysis, and distinguish between stochastic and structural poverty. The definition of poverty groups matters for policy makers because it can improve the targeting of households and identify structurally vulnerable households (not just temporarily misfortuned ones) when designing conservation policies.

This paper introduces a new approach to analyze forest-poverty interaction from cross-sectional household data. We use a wide range of household assets and characteristics in a regression model to predict income, in what we label an augmented asset approach. We take this predicted income to be the normal or expected income of the households. We then combine households' observed and predicted incomes and obtain four different poverty categories (structural/stochastic poor/non-poor). By distinguishing between stochastic and structural poverty, we demonstrate how certain dynamic aspects of forest reliance and poverty can be analyzed even without panel data. We do this by first testing the commonly observed relationship: are poor households more forest reliant (high relative forest income) while better-off households have higher absolute income from the forest? Second, we explore how the answer to this question is sensitive to the method used to categorize households. Third, we show how the distinction between structurally and stochastically poor can yield new insights into the role for forests in rural livelihoods.

A key insight of this paper comes from separating between the structurally and stochastically poor/non-poor households. We confirm the commonly found pattern that the poor households are the most forest reliant. When differentiating between categories of poor households, we find forest reliance to be high among households that are poor in both assets and observed income (structurally poor), but it is even higher among households that are categorized as stochastically non-poor. Households in this category have high incomes in the survey year, but we do not expect them to be able to sustain this high level of income due to low levels of productive and human assets. In fact, this last group, the stochastically non-poor, are the ones expected to be the most forest reliant in the longer term, because they are not only forest reliant, but also derive high absolute values of income from forest resources.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the study context, design and the data collection. We define the key terms and describe the methods used for data analyses in Section 3, while the results of the analyses are presented and discussed in Section 4. In Section 5, we conclude the paper and provide some policy recommendations.

2 Study context and data collection

We conducted the study in Kilosa District in the Morogoro region in Tanzania in 2010. The district has an area of 14 245 km^2 and had a population of 488 191 in the latest (2002) census. Agriculture is the main income generating activity, employing about 85% of the labor force (URT, 2007).

Forests cover approximately 52%[1] of the land in Kilosa district (URT, 1997). According to the statutory tenure system in Tanzania, the state is the *de jure* owner of all land. Although the state has retained the right to alienate property rights, approximately 10% of all forest is under some form of participatory forest management, meaning that some rights are decentralized to communities (Sunderlin et al., 2008). All villages in our sample have community rights to at least parts of the forested areas within the village boundaries, and households have the rights to harvest forest resources, either by statutory or customary laws. User rules and regulations exist; both commercial

[1] The exact number is unknown (URT, 2007), and different estimates are reported in the literature. Our estimate is based on 1997 figures (URT, 1997).

and subsistence uses of timber are regulated, as well as commercial use of NTFPs. Harvesting of NTFPs for subsistence use is permitted in all villages, except within state forest reserves[2].

Our data set is part of the Global Comparative Study on REDD+ (GCS-REDD) conducted by the Center for International Forestry Research (CIFOR) and its partners. Kilosa is one of the six study sites in Tanzania[3]. Three of the villages are included as pilot projects of the global effort aimed at Reducing Emissions from Deforestation and forest Degradation (REDD+), implemented by a national NGO. These villages were selected randomly from all villages included in the project. The last two villages were selected as controls from a pool of other villages in the district, based on how well they matched on a set of village level variables, including market access, population pressure and tenure rights, such as some level of community rights to the forest within the village boundaries (Sunderlin et al., 2010).

We use data from a sample of 149 randomly selected households in the five villages. Detailed information on household characteristics, asset holdings and incomes was recorded through household surveys in July and August 2010. If possible, both the head of household and the spouse were present if the head of household was married. While several surveys throughout the year might give more precise income estimates (Angelsen et al., 2011), this was not feasible within the large, multi-country GCS-REDD project that this survey was part of. We did, however, train enumerators in techniques to facilitate more exact recall during the interview, for example, by decomposing income calculations by asking questions for each agricultural season.

3 Methods

3.1 Income and assets calculations

Total income is defined as the sum of cash income, subsistence income (i.e. value of household consumption of self-produced or self-collected goods), and net (cash or in-kind) gifts and transfers. The accounting methods from different sources of incomes draw on Cavendish (2002) and the PEN survey (Angelsen et al., 2011). We use local market prices when available. Some goods, particularly environmental goods, are for self-consumption and not traded. We then used own reported values to get a more realistic estimate of the real price (value to the household) rather than inflated prices in

[2] For an overview of forest tenure rights in Tanzania, see Blomley and Ramadhani (2006).
[3] For more details about the project, see http://www.cifor.org/gcs/global-comparative-study-on-redd.html

a faraway regional market (Wunder et al., 2011). To calculate income from each source we deduced the cash costs of purchased inputs (e.g., hired labor, seeds and fertilizer for crops and medicine for livestock) from the product value (price * quantity collected or produced). The value of family labor is *not* deducted, and should not either, based on the standard definition of household income.

For all agricultural, forest and livestock products, we checked total values and prices. We reviewed outliers in collaboration with the enumerators in the field and compared with village mean price after data entry. In the case of a missing price, we used the mean village price. Given restrictions on the harvest in protected areas or of certain products, such as woody material for production of charcoal, some activities are illegal and may be underreported in the household surveys. We are not able to test or control for this potential bias in our data, but tried to limit this during data collection by underscoring to respondents that none in our group of field workers were linked to government or any environmental NGO and that the households' information would remain confidential.

There is a range of methods to account for differences in household size and composition and thereby different consumption needs across households (Deaton, 1997). We use income variables as per adult equivalent units (AEU), adapting a simple version whereby adults aged 15-64 are given full weight (1) while dependents (below 15, above 64) are given half a weight (0.5). Operational agricultural land holding is also divided by AEU. To facilitate comparison with other studies, income is reported in purchasing power parity (PPP) adjusted 2010 US dollar.

The households' liquid assets include livestock, business capital stock and household and farm implements. These are assets that can readily be sold to obtain cash. The value of these items were estimated by asking for the current sale price of the item, taking into account the age and condition of the asset. We did not collect information about cash savings, but assume (based on non-systematic information) that most savings are in livestock and other assets rather than cash.

Crop income is by far the main component of the total household income, accounting for about two thirds of the income in the study villages, followed by forest income (Table 1)[4]. The mean forest reliance – the share of forest environmental income on total household income - among the households in the sample is 13%. The single most valuable forest product is firewood.

[4] We also recorded negative income for some households, e.g., were they have had large input costs for crops but experienced a crop failure.

Table 1
Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Share (%)[b]
Household income (in USD[a])						
Total household income	149	1 361	1 443	144	12 796	
Total household income, per AEU	149	371	413	41	3 656	
Crops	149	249	296	-17	2 020	66.6
Business	149	42.88	210	0	2311	5.7
Forest	149	31.29	40.44	0	279	12.9
Firewood	149	19.88	20.16	0	116	8.9
NTFPs	149	5.44	17.13	0	142	2.1
Timber prod, incl. charcoal	149	5.97	31	0	258	1.8
Wage	149	21.43	107.19	0	1236	5.8
Non-forest environmental	149	16.13	46.86	0	501	6.2
Livestock	149	5.33	25.07	-118	189	1.6
Miscellaneous	149	4.36	13.76	0	100	1.3
Human capital assets						
Household size (#)	149	5.12	2.07	1.00	14.00	
AEU (#)	149	4.00	1.59	1.00	9.50	
Age household head (years)	149	45.51	14.44	20	98	
Education household head (years)	149	4.42	2.95	0	11	
Illness household head (days)	149	11.51	22.93	0	182	
Illness spouse (days)	149	7.50	14.64	0	90	
Female head (0-1)	149	14%				
Wage income (0-1)	149	26%				
Household business (0-1)	149	18%				
Charcoal producers (0-1)	149	7%				
Productive and liquid assets						
Agricultural land per AEU (ha)	149	0.50	0.34	0.08	2.02	
Hh/farm implements (USD)	149	108	185	0	1628	
Oxen & other large animals (#)	149	0.03	0.41	0	5	
Sheep & goats (#)	149	0.70	2.74	0	24	
Chicken (#)	149	9.13	10.64	0	64	
Contextual variable						
Distance to village center (min)	149	93.00	87.86	0	360	

[a] PPP adjusted 2010 exchange rate: 2010: 1 USD = 515.87 TSH (http://www.econstats.com/weo/V013.html).
[b] The mean income shares are calculated by taking the mean income shares for the households.

3.2 *Observed versus Predicted Income*

Using a one-year income only provides a static picture of the households' economic status and fails to take into account the dynamics of poverty (see e.g., Hulme and Shepherd, 2003). While some households are consistently poor, others might have been unlucky that particular survey year, but had a higher income the previous year and are expected to have a higher income the next year. Likewise, some households that normally have incomes below the poverty line might have had a bumper harvest in the survey year. Nielsen et al. (2012) present a simple framework to take some of the dynamics aspects of poverty into account the when studying poverty-environment relations in cross-section data, based on the observed household income and liquid asset holdings. A limitation of their approach is that they use only a subset of assets. Agricultural crop income is the dominant income source in our sample, similar to most rural households in Africa (Angelsen et al., 2014; Davis et al., 2010), and thus the amount of land and labor are important productive assets. Human capital assets, such as health and education are potentially important for household income as well as income diversification. Similarly, context variables, such as remoteness of the household, infrastructure and access to markets may also be important. We therefore use an augmented asset approach to predict household income, including liquid and non-liquid assets, human capital assets as well as household characteristics and contextual variables. We argue that the resulting predicted income is a better measure for the poverty status of a household. Further, the regression coefficients are estimates of the relative importance of various assets in generating income, and one thereby avoids the problem of converting all assets into monetary value.

3.3 *Estimating Predicted Income*

To predict household income, we estimate the following log-linear[5] regression:

$$lnY = \beta_0 + \beta_1 Householdcharacteristics + \beta_2 Assets + \beta_3 Distance + \beta_6 Village + u \quad (1)$$

Income is log-transformed (*lnY*) to account for non-normality in the distribution and to reduce the impact of outliers.[6] *Householdcharacteristics* is a vector of household characteristics we expect to be

[5] The main purpose of predicting income is to categorize households into poverty categories, and as a robustness test we predict income based on a model where all continuous variables are log-transformed, see Appendix. The pattern of forest reliance is stable across the household categories with the alternative functional form to predict income.

[6] One household has negative total net income because of high costs related to agricultural production; this household is not included in the regression and reduces our sample to 149 households.

correlated with household income, including number of adult males, adult females, elderly, young and children. We expect households with more adults to have higher total income due to more available labor. The number of children may have a negative effect on household income, as this might require more time set aside for care and other non-productive activities. A dummy variable for gender of the household head is also included in the vector, along with the age and the squared value of age to accommodate for any non-linear effects. We expect younger household (heads) to focus on establishing a family and spend time taking care of children until a certain point, where children are older. Age can also be linked to skills and physical strength, which can co-determine income. The number of years the household head has been in school is included. We expect more educated household heads to have higher incomes due to better skills, better access to information and off-farm income generating activities.

We also included three dummy variables for the households' involvement in relatively lucrative income generating activities: household business (such as selling locally brewed beer or transporting locally produced agricultural goods to the market by bicycle), off-farm work (receiving wage, either from permanent or casual labor), and charcoal production. Finally, health is expected to affect total household income negatively, and the number of days the household head and spouse were ill in the previous 12 months are included as proxies of health.

Assets is a vector of productive, liquid and non-liquid assets, all expected to be positively correlated with household income. Crop income is the main source of income for most households, and agricultural land is an important productive asset. Size of land measured in hectares (ha) that the household had access to cultivate at the time of the survey, and includes owned land not rented out and rented in land. The total value of farm and household implements (in PPP adjusted 2010 US dollar) is included, as well as the number of livestock (differentiating between large, medium and small).

Distance is the walking time from the residence to the village center (in minutes), and we expect remote households to have lower total incomes. To control for village specific variations in income, infrastructure and market access. *Village* dummies are included to capture any systematic locational differences not captured in the other variables.

3.4 Categorizing Households

We use two approaches to categorize households. The first approach is to divide the sample into five quintiles based on either observed or predicted income. Although most households in our sample are poor in a macro context, the focus of this paper is inter- and intra-village variation, and households are categorized from poor to non-poor relative to the other households in the sample. As a measure of the poverty profile of forest income, Vedeld et al. (2004) suggest using the Kuznets Ratio; the ratio between the mean forest income for the 20% highest-earning households and the mean forest income for 40% lowest-earning households. If the ratio is below 1, low-income households have higher mean forest income. We calculate the both the Absolute Kuznets Ratio (absolute forest incomes) and the Relative Kuznets Ratio (forest income shares).

The second approach is to categorize households based on both observed and predicted total income. Carter and May (2001) distinguish between stochastic and structural poverty. Following their categorization, households are defined as (i) structurally poor if they have low observed and low predicted income, (ii) stochastically poor if they have low observed income and high predicted income, (iii) stochastically non-poor if they have high observed income and low predicted income, or (iv) structurally non-poor if they have high observed income and high predicted income.

Characteristics of households are compared across quintiles and the household categories. We compare means of variables and use one-way ANOVA with Bonferroni and Kruskal-Wallis tests to assess statistical significance.

4 Results and Discussion

4.1 Predicted Income

The results of the regression model used to predict income are reported in Table 2. We obtain a relatively high R^2 value and explain 52% of the variation in total income. In general, households with high income tend to have more productive males and females and household head has longer education. The coefficient for age is negative while the coefficient for squared age is positive. The turning point is 44.5 years in a U-shaped relationship, meaning that income is decreasing with age until 44.5, and then increasing with age. This may be an effect of higher care-taking responsibilities and thus lower incomes in families with younger heads of households.

Table 2
Regression of log of total household (hh) income (in PPP adjusted 2010 USD)

Variables	Coefficients (robust SE)
Household characteristics	
Adult males in the hh (aged 16-64)	0.1585 (0.0646)**
Adult females in the hh (aged 16-64)	0.1571 (0.0690)**
Elderly in the hh (aged 65 and above)	-0.0242 (0.1771)
Young in the hh (aged 10-15)	0.0825 (0.0643)
Children in the hh (aged 9 and below)	0.0021 (0.0475)
Age of household head (years)	-0.0459 (0.0238)*
Age of household head (years squared)	0.0005 (0.0003)**
Education household head (years)	0.0484 (0.0185)**
Illness household head (days)	-0.0047 (0.0029)
Illness spouse (days)	-0.0028 (0.0032)
Female head (0-1)	0.1234 (0.1686)
Wage income (0-1)	0.0980 (0.1508)
Household business (0-1)	0.4901 (0.1418)***
Charcoal producers (0-1)	0.1306 (0.1986)
Household assets	
Agricultural land (hectares)	0.1950 (0.0566)***
Hh/farm implements (USD PPP)	0.0007 (0.0003)**
Oxen & other large animals (#)	-0.0753 (0.0952)
Sheep & goats (#)	0.0234 (0.0166)
Chicken (#)	0.0187 (0.0048)***
Contextual variables[b]	
Distance to village center (min)	-0.0020 (0.0006)***
Constant (intercept)	6.4317 (0.5547)***
R^2	0.5225
N	149

*, **, *** significant at 0.1, 0.05 and 0.01 levels. [a] Values reported are the coefficients from a log-transformed dependent variable. To interpret the effect, take the exponentiated coefficient. [b] Controlled for village fixed effects by including village dummy variables, but these are not reported in the Table.

Further, households with business incomes have approximately 63% higher incomes compared to households with no business income. Agricultural land is the main productive asset, and households with more land have higher total incomes. The exponentiated coefficient for land is

1.22, indicating that households with one hectare more have on average 22 percent higher total incomes. Among the liquid assets, households with more farm and household implements have slightly more total income, while the number of chickens is the only significant variable among the livestock variables. While this might look surprising, it might be explained by the fact that only a small number of households keep large and medium livestock in our sample (only 17 households keep sheep and goats). Households further from the center of the village have lower total incomes. All these results are in line with expectations, and since the main purpose of the model is to predict income, we do not discuss them further.

By definition, predicted income varies less than the observed income; we cannot predict an income loss due to crop failure or a 'positive income shock' due to a bumper harvest, and the maximum predicted income is less than half the observed income (Table 3). The difference in mean observed and predicted income is due to the smearing estimate. When transforming the income variable back from log to the level variable to estimate the predicted income, we adapt the smearing estimate developed by Duan (1983) to avoid the retransformation bias and underestimation of predicted income.

Table 3
Observed and predicted household income (USD PPP, per AEU)

Variable	Obs	Mean	Std. Dev.	Min	Max
Observed total income	149	371	413	41	3 656
Predicted total income	149	366	243	82	1 429

There are a number of potentially relevant but unobservable household characteristics, which may bias our results. We are, for example, not able to predict total household income well for the households with high forest income. The correlation coefficient between the error term of the predicted income and forest income is 0.17, which indicates that predicted income is systematically lower for households with high forest income.

4.2 Forest Reliance across Observed and Predicted Income Quintiles

As expected, forest reliance (as measured by the share of observed income) is negatively correlated with observed total income (-0.26, Table A.1). This pattern is also shown in the top panel of Table 4. The findings are supported by the Kuznets Ratios. The Relative Kuznets Ratio is 0.27, i.e., forest reliance among the poorest 40 % is close to four times higher compared to the top 20%. On average, households in the highest income quintile earn 5% of their total income from forest, compared to 18% in the lowest quintile. Compared to other studies, including the comparative work reported in Angelsen et al. (2014), the pro-poor profile of forest reliance is very strong in our Tanzanian sample.

Table 4
Comparison of mean incomes (USD PPP, per AEU), value of assets and forest reliance across poverty quintiles constructed based on observed and predicted income

	Q1	Q2	Q3	Q4	Q5	Test statistics[a]	Kuznets Ratio
Observed income quintiles							
Observed income	104	161	245	379	957	F=45.88***	
Predicted income	205	258	306	371	685	F=34.39***	
Value of liquid assets	167	129	214	428	794	F= 9.62***	
Absolute forest income	18.50	25.25	25.87	52.47	33.96	F= 3.31**	1.55
Forest reliance	0.18	0.16	0.11	0.15	0.05	F= 4.26***	0.27
Predicted income quintiles							
Observed income	149	215	293	370	820	F=17.87***	
Predicted income	150	217	285	408	763	F=145.04***	
Value of liquid assets	87	195	264	420	763	F=8.51***	
Absolute forest income	21.17	35.93	43.70	24.52	30.81	NS	1.03
Forest reliance	0.16	0.20	0.16	0.09	0.05	F=5.21***	0.24
N	29	30	30	30	30		

*, **, *** significant at 0.1, 0.05, and 0.01 levels respectively. [a] One-way ANOVA

While households in the lowest income quintile earn a higher share of their total income from forest resources, households in the highest quintiles have higher forest income in absolute terms. The Absolute Kuznets Ratio is 1.55, i.e., the mean absolute forest income among the households in the top income quintile is 55% higher than in the two lowest quintiles. However, total income is not correlated significantly with absolute forest income (correlation coefficient 0.032). This can in part be explained by the fact that the highest forest income is among the households in the second richest income quintile, where the majority of the households producing charcoal are found.[7]

[7] This also illustrates a weakness of the Kuznets ratio, namely that it ignores two middle-income quintiles (40-80%), and in our case "much of the action" (highest forest use) is happening here.

The mean absolute forest income is lowest among the households in the first quintile while they also have the highest observed forest reliance at 18%, reflecting their low total income. The households are not expected to continue to have this low income in the future, and their predicted income is more than twice as high. Thus, if the harvest of forest resources is more stable, their long term forest reliance is lower than what we observe.

Using quintiles based on predicted income, the overall pattern of observed forest reliance is similar to the pattern we found across the observed income quintiles, and the Relative Kuznets Ratio is even lower (0.24). The differences across the alternative measures of forest reliance are smaller, because there are smaller differences between observed and predicted income across the quintiles.

When comparing the absolute forest income across quintiles of predicted income, however, the pattern is different. There is no significant difference in mean absolute forest income across the quintiles, and the correlation coefficient between absolute forest income and predicted total income is virtually zero (0.01). This is also supported by an Absolute Kuznets Ratio very close to unity (1.03). Whereas most studies find that absolute forest income is highest among the richest households, we find no such distinct pattern. This suggests that comparing households based on predicted income may provide new insight in the poverty-environment analysis. A seemingly minor change in the way to categorize households leads to a qualitatively different results in our case.

4.3 Poverty Categories

Combining the categorization based on observed and predicted incomes enables a further analysis of the poverty-environment relation. We use the four household categories discussed earlier: structurally poor, stochastically poor, stochastically non-poor, and structurally non-poor (Table 5). We define the cut-off line between high and low income between quintile 3 and 4, meaning that 60% of the households are defined as low income (poor) households. This cut-off line is close to the commonly used poverty line of "a dollar a day"[8]. Further, the mean observed income is not significantly different across the three lowest income quintiles while the mean observed income among the households in the fifth quintile is significantly higher than all others. Mean income in the fourth quintile is significantly higher than mean income in the two lowest quintiles.

[8] If we apply a rural poverty line below this, at 1 USD/day, we get a poverty line at an annual income of 188 293 TSH with a 2010 PPP conversion rate at 515.87 (http://www.econstats.com/weo/V013.htm). This threshold is found at the beginning of the fourth quintile for both observed and predicted income.

Table 5

Comparison of households' rank in observed and predicted income quintiles

Observed income quintiles	Predicted income quintiles					
	1	2	3	4	5	Total
1	14	9	6	0	0	29
2	10	8	4	7	1	30
3	2	7	12	7	2	30
4	3	5	6	11	5	30
5	0	1	2	5	22	30
Total	29	30	30	30	30	149

Structurally poor
Structurally non-poor
Stochastically non-poor
Stochastically poor

A methodological note is in order here. In a typical econometric analysis, Table 5 would be used to test the performance of the model, i.e. to what degree households are correctly predicted to belong to different income classes. We are less interested in that aspect in our analysis. Rather, having included a broad set of variables hypothesized to determine income, we use the difference between the observed and predicted income (the error term) as an indicator of to what extent there was a random income fluctuation due to, for example, positive or negative shocks in the survey year. If the regression model gave a very good prediction of income with R^2 close to 100%, implying small temporal income fluctuations, our approach would have limited utility. If, on the other hand, the model predicted poorly with R^2 below, say, 10%, that would question the usefulness of even using terms such as predicted or normal income. This is not to say that R^2 close to 50% (52% in our model) is optimal in some sense, it depends on the actual temporal income variation in the study area.[9]

Among the 29 households in the lowest observed income quintile, only half are in the lowest quintile for predicted income (Table 5). The 17 households that have low observed income but high predicted income is not expected to stay poor in the long run, and are thus categorized as stochastically poor.

[9] A limitation with our approach is the likely existence of unobservable variables that affect incomes (e.g. farmers' skills). This might explain some portion of the difference between observed and predicted income. This is a general problem in cross-sectional data analyses, which can only be solved properly by using panel data. However, compared to the conventional focus of using only observed income, or solely assets as determinants of income, our proposed approach is a step forward.

With the exception of forest income, the structurally non-poor earn higher incomes from most of the income sources (Table 6).

Table 6
Comparison of income (USD PPP, per AEU) and key characteristics across household categories

	Structurally poor n=72	Stochastically poor n=17	Stochastically non-poor n=17	Structurally non-poor n=43	Test statistics[a]
Income variables					
Crops	107	139	328	501	F=25.64***
Business	4.21	6.75	0.00	138.87	F=4.51***
Forest income	24.96	16.03	70.91	32.27	F=7.78***
Firewood	18.57	13.64	18.19	25.22	NS
NTFP	4.66	1.86	17.81	3.27	F=3.67**
Timber/charcoal	1.74	0.52	34.91	3.78	F=6.33***
Wage	13.58	12.87	24.62	36.70	NS
Non-forest environmental	10.37	13.90	18.60	25.69	NS
Livestock	4.03	0.02	2.53	10.72	NS
Miscellaneous	1.24	4.29	5.69	9.06	F=3.08**
Total income	165	193	451	754	F=31.63***
Predicted total inc.	210	456	253	637	F=73.37***
Forest reliance	0.16	0.09	0.20	0.06	F=6.70***
Share commercial forest inc.	0.02	0.06	0.08	0.01	NS
Household characteristics					
AEU (#)	4.44	3.47	3.85	3.53	F=3.92**
Female headed (0-1)	0.11	0.24	0.29	0.09	NS[b]
Age (years)	45.99	46.29	47.00	43.81	NS
Education (years)	3.92	4.35	3.82	5.51	F=3.02**
Agricultural land (ha per AEU)	0.34	0.74	0.40	0.71	F=18.95***
Value liquid assets (USD PPP)	163	202	270	746	F=14.15***
Illness household head (days)	11.29	19.65	10.06	9.23	NS
Illness spouse (days)	8.44	5.71	4.00	8.02	NS
Dist. to village center (min)	120	56	88	64	F=5.21***

*, **, *** statistical significance at 0.1, 0.05 and 0.01. NS=Not significant. [a]One-way ANOVA with Bonferroni. [b]Kruskal-Wallis equality of population rank test for this non-parametric variable.

The structurally non-poor are also the most educated group, have more liquid assets and have significantly more land than the structurally poor and stochastically non-poor households. Distinguishing between structurally and stochastically poor/non-poor households yields additional insights into the patterns of forest reliance. Households categorized as stochastically non-poor earn the highest absolute income from forest, and they are also the most forest reliant. This finding differs from most studies of forest reliance, which identify the poorest households as the most forest reliant. This include studies categorizing households based on observed income only, such as Heubach et al. (2011) and Rayamajhi et al. (2012), but also Nielsen et al. (2012) who combine income and liquid asset holdings. The pattern of forest reliance is stable across household categories with the alternative functional form to predict total income (Table A.2).

The stochastically poor households have low observed income, but high predicted income. We do not have data to test explicitly whether these households have in fact experienced a shock during the previous year. On average, these households have been more prone to illness (household head), but the difference in is not significant across the household categories. They have on average more than twice the land compared to the structurally poor and still there is no significant difference in crop incomes. This indicates an agricultural income shock, or that the households for some other reason have not been able to make the full use of their productive assets. Some studies find that forest income serve as a safety net after an income shock (Pattanayak and Sills, 2001; Debela et al., 2012). If the incidence of income shocks is higher among the stochastically poor, we might therefore expect higher forest incomes in this group, but we find no evidence of this. The lack of evidence of a safety net function of forest income among the stochastically poor in our sample might be explained by how we define this group. The stochastically poor households have, by definition, relatively high asset holdings, and might therefore have other means to cope with shocks. Debela et al. (2012) find that asset poor households use the forest to cope with large shocks, while households with more land and non-land assets are less likely to rely on forest in the case of a shock. This is similar to the findings in the global comparative study on the role of forests as a safety net by Wunder et al. (2014).

The stochastically non-poor households have less agricultural land, are less educated, have less liquid assets and earns less income from crop compared to the structurally non-poor households. They are both the most forest reliant and have the highest absolute forest income among the four household categories. Some of the difference is due to higher incomes from non-timber forest products (NTFPs), but the main explanation is the higher incomes from timber and charcoal for some households in this group.

The stochastically non-poor have, on average, higher crop income per unit of land, and this is the main difference compared to the structurally poor. This can be due to higher yields, higher prices, or a combination of the two. The two most important crops (in terms of income) are maize and beans. Maize is mainly for subsistence use, while the households producing beans on average sell 52% of their output. Yet we find little variation in the price of a sack of maize across the different household categories. The average price of beans is 13% higher among the stochastically non-poor compared to the structurally poor (Table A.3). The difference is not significant, but can still be an indication that the households in this group are able to get a higher price for some marketed agricultural crops. Still other explanations that we are not able to fully test with the available data seem likely to explain the difference in output value per hectare, including unobservable inputs such as managerial and agronomic skills and soil quality.

If households in the stochastically non-poor category have been able to engage in highly productive and profitable agricultural activities or have other productivity-enhancing characteristics that we have not measured, their higher-than expected income levels might not necessarily be temporary. The prices received for marketed crops may not vary randomly across households, but may be due to better relation with buyers, better information about prices in different markets, or richer households being able to time the sale of their produce (e.g., not sell immediately after harvest when prices tend to be lower). Similarly, the stochastically non-poor may be in a better position to make use of communal resources to engage in extraction with high-return forest products, as use of communal resources is not included in households' reported asset holdings.

Finally, there are variables such as entrepreneurial and managerial skills that are hard to measure. We have included a few household characteristics in the regression model, including whether or not the households run their own business, but there is likely to be others that are important for future income. To the extent this is an issue, the category "stochastically non-poor" will be misleading. This is a limitation of the proposed approach, and with only access to cross-section data we cannot test how well we predict future income.

5 Conclusions

This paper aimed to explore the implications of an alternative income measure and household categorization on frequently asked questions about forest and poverty. While we fully realize that nothing can replace observing the same households over time to get panel data, we believe the suggested method can be used to discuss some aspects of poverty, normally confined to analysis of poverty dynamics with long-running panel data. The approach used can therefore be highly valuable given that most datasets are based on one-shot surveys.

Categorizing households based on observed income yields the conventional finding that the poorest households are more forest reliant, while the better off use more forests products in an absolute sense, although the differences are not as distinct as found in most other studies (e.g., Angelsen et al., 2014). But this result is sensitive to how we categorize households: if categorized based on predicted income, the predicted poorest are more forest reliant, but the better-off households do not use more forest products in an absolute sense. The new categorization therefore changes a major conclusion in the forest-poverty literature for our case.

The reasons for the changing result can best be understood when we take the categorization a step further and categorize households based on both observed and predicted income into four stochastically/structurally poor/non-poor groups. This separation yields valuable new insights. One group stands out in terms of having both the highest forest reliance and absolute forest income, namely the stochastically non-poor. These asset poor (land in particular) households have enjoyed a high total income in the survey year, but have also significantly higher forest income. These high forest-users are not categorized as poor when using observed income, but are when using predicted. On the other hand, the stochastically poor households, those that are relatively asset rich but happen to have low income in the survey year, are not intensive forest users.

While the study and analysis was not designed to look into the role of forests role as shock absorbers and a possible pathway out of poverty, the results may shed some light on this debate. First, forests did not play any significant role for the asset rich households that experienced an income shortfall. This group seems to have other coping options, and is not the most vulnerable group for the type of income shocks that our analysis suggest. That group would be among the asset poor. Second, the stochastically non-poor households are able to enjoy a higher than predicted income. Although higher crop income is the main explanation, forest income also contributes to making these households move out of the structurally poor category. Our analysis is not suitable for studying the potential of forest income as a pathway out of poverty. Long-term panel data is needed to study this, but we cannot rule out that at least for some households, commercial forest activities can play a role.

The proposed method enables us distinguish between households that are observed to be poor because they are experiencing a temporary income shortfall and can be expected to recover in the future, and those that are observed to be poor because that is the normal state. This has policy implications for targeting poverty alleviation in general, but also for how vulnerable the different groups are for changes and restrictions in access to forest resources. While the structurally poor can be characterized by high forest reliance, the stochastically poor households have no different pattern of forest resource use compared to the structurally non-poor, neither when we compare forest reliance nor absolute forest income. Thus, these households are less likely to be vulnerable than the structurally poor and also the stochastically non-poor. The focus in the vulnerability analysis should therefore shift from observed "snap-shot" income to predicted income based on an augmented asset approach, in order to minimize the effect from temporal income fluctuations.

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Appendix

Table A.1: Correlation matrix for different measures of total income, value of assets, forest income and forest reliance

	Observed total income	Predicted total income	Value of Assets	Forest income	Forest reliance
Observed total income	1.0000				
Predicted total income	0.6113*	1.0000			
Value of Assets	0.2905*	0.5578*	1.0000		
Forest income	0.0320	0.0149	0.0138	1.0000	
Forest reliance	-0.2624*	-0.2980*	-0.1684*	0.7588*	1.0000

*Significant at 0.05 level

Table A.2: Comparison of variables across household categories based on observed income and predicted income (log-log model*)

	Structurally poor n=71	Stochastically poor n=18	Stochastically non-poor n=18	Structurally non-poor n=42	Test statistics[a]
Income variables (AEU)					
Crops	104	146	308	513	F=27.25***
Business	4.64	4.90	0.00	142.18	F= 4.69***
Forest income	24.06	20.07	68.28	32.47	F= 7.01***
Firewood	19.26	11.17	18.16	25.39	F= 2.29*
NTFP	3.36	7.15	17.14	3.21	F= 3.63***
Timber/charc.	1.45	1.74	32.97	3.87	F= 5.83***
Wage	13.94	11.49	23.25	37.58	NS
Non-forest env	10.10	14.75	17.43	26.36	NS
Livestock	4.03	0.24	3.06	10.69	NS
Miscellaneous	1.53	2.98	11.21	6.78	F= 3.11***
Total income	163	201	431	769	F=33.40***
Predicted total inc.	214	427	305	624	F=53.16***
Forest reliance	0.16	0.11	0.19	0.06	F= 5.96***
Share commercial forest inc.	0.03	0.03	0.07	0.01	NS
Household characteristics					
AEU (number)	4.45	3.47	3.86	3.52	F= 4.09***
Female headed	0.13	0.17	0.33	0.07	NS[b]
Age (years)	46.61	43.83	50.44	42.26	NS
Education (years)	4.03	3.89	3.67	5.62	F= 3.49***
Agricultural land per AEU	0.33	0.73	0.41	0.71	F=19.41***
Value liquid assets (USD PPP)	162	204	340	727	F=12.55***
Illness hh head	10.06	24.06	10.33	9.10	NS
Illness spouse	6.92	11.89	3.78	8.21	NS
Dist. to village center (min)	117	72	72	71	F= 3.50***

*Income predicted based on log-log model (variables on log form in the regression model: member groups of household, year education of household head, illness head and spouse, land, farm and household implements, livestock, distance).

[a]One-way ANOVA with Bonferroni.

[b]Kruskal-Wallis equality of population rank test for this non-parametric variable.

Table A.3: Comparison of crop prices across household categories

Price of crops (gross value per sack, in USD)	Structurally poor	Stochastically poor	Stochastically non-poor	Structurally non-poor	Test statistics
Maize	53	51	49	50	NS
Beans	162	161	185	174	NS