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Assessing the determinants of poverty and vulnerability of smallholder farmers in a changing climate: the case of Morogoro region, Tanzania

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Abstract　This paper analyses the determinants of poverty and vulnerability of smallholder farmers in the rural areas in the face of climate change. The data were collected through a cross-sectional survey conducted between December 2009 and January 2010 covering 240 households in six villages of Morogoro region, Tanzania. Descriptive and the econometric approaches involving three-stage least squares (3SLS) and generalized methods of moments (GMM) regressions were used to analyse poverty and vulnerability. Results indicate that income poverty was prevalent in the study area—based on a daily income per capita poverty line of US$ 1.25. The income poverty was relatively higher in agro-climatically less-favourable area than in favoured areas. Over three quarters of the sample households were vulnerable. The pattern of future vulnerability tended to overlap with poverty rates. Ageing of the household head tended to increase the level of vulnerability. Large-sized households were more income-poor than their counterpart small-sized households. Farming experience reduced the probability of future vulnerability. Increased farm size enhanced the level of income, and further increase in farm size reduced future vulnerability. Higher income contributed to wealth formation through improved access to assets and housing amenities. Farmers who perceived that climate change is human-induced tended to have significantly higher income than otherwise. The following conclusions with policy implications are drawn from the findings: (1) addressing poverty and vulnerability of farmers is critical particularly in relatively agro-ecologically less-favoured areas that are prone to climate change impacts, (2) old-age-related vulnerability must be addressed through dedicated policies and programmes, (3) increasing farm size would enhance smallholder farm income, (4) awareness creation among farmers on climate change drivers and processes by highlighting anthropogenic contribution is important in order to influence local adaptation and mitigation practices, and (5) improving rural income will advance wealth creation and foster local livelihood resilience to shocks including climate change.

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Introduction

Climate change is an additional multiplier of the detriments of poverty and vulnerability in developing countries

particularly those in sub-Saharan Africa (AfDB et al. 2003; Meena et al. 2006; Munasighe 2010). The livelihoods of the majority in the sub-Saharan Africa are dependent on agriculture. Agriculture is one of the human activities most dependent on climate, and as a result it is one of the sectors where climate change impacts are expected to hit hardest (Hertel et al. 2010). The impacts of climate change, and the vulnerability of poor communities to climate change, vary greatly, but generally, climate change is superimposed on existing vulnerabilities (AfDB et al. 2003).

A quarter of the population of developing countries still lives on less than $1.25 a day (Munasighe 2010). Addressing poverty is going to be harder with climate change that will make poverty deeper particularly in tropical dryland areas of Africa that host farmers and herders who depend on climate-sensitive agriculture for their livelihood (Hatibu et al. 2006; Pouliotte et al. 2009; Thomas et al. 2007; IFAD 2011). About three quarters of Tanzania characterized by semi-arid to sub-humid climates experience erratic rainfall (Bourn and Blench 1999; Hatibu et al. 2006). Even 2 °C warming above preindustrial temperatures—the minimum the world is likely to experience—could result in permanent reductions in GDP of 4–5 % for Africa and South Asia (World Bank 2010; Munasighe 2010).

In Tanzania, temperatures are predicted to rise to 2–4 °C by 2100, warming more during the dry season and in the interior semi-arid and sub-humid regions of the country including Morogoro (Paavola 2008). The interior regions are also expected to experience a reduction in precipitation up to 20 %, prolonging the dry season and increasing the risk of drought (Hulme et al. 2001; Paavola 2008). Based on the four GCMs (i.e. ECHAM5, CRNM-C3, MIROC 3.2 and CSIRO Mark 3) under A1B scenario, Kilembe et al. (2013) predicted a widespread negative impact in terms of maize yield loss under rainfed condition of between 5 and 25 % from the 2000 baseline over the Morogoro region by 2050. Another recent study was done by Tumbo et al. (2014) covering sub-humid parts of Morogoro used an integrated climate change impact assessment involving an ensemble of five CMIP5 GCMs, two crop models (DISSAT and APSIM) and an economic model (ToA-MD)—based on representative concentration pathways (RCPs) 8.5 (see Riahi et al. 2011; Thomson et al. 2011) by mid-century (2040–2069) climate scenario and 2010 baseline. Tumbo et al. (2014) predicted that without adaptation (i.e. under business-as-usual), the future climate change by mid-century will impact on the local cropping systems and as a result increase the income poverty rates among farmers by 15 % from the 2010 baseline. Even in areas of predicted increased precipitation, the expected seasonal shifts and floods will still render dryland farming riskier. According to Hatibu et al. (2006), such climate risks limit smallholder

farmers to take advantage of opportunities arising from emerging markets, trade and globalization.

The climate change–poverty nexus is indisputable and strongly correlated with adaptation and development (Tanner and Mitchell 2008; Bremner et al. 2010). Poverty and vulnerability to climate risks are not the same, but there are significant overlaps (Nelson and Stathers 2009). Risk and uncertainty are a central preoccupation of the poor (World Development Report 2001). For an agriculture-dependent country like Tanzania, where poverty is sensitive to food production and food production is sensitive to climate, rising climate volatility has implications for poverty vulnerability (Ahmed et al. 2011). The poor have become increasingly vulnerable to the physical impacts of climate change through reduced income and declining food security (Pouliotte et al. 2009).

A decade of research on climate change vulnerability shows us that inevitably it is the poor and the most vulnerable who suffer the impacts of changing environmental conditions—hence climate change has to be mainstreamed in the development process (Tompkins and Adger 2003; Stern 2007; Collier et al. 2008; Mendelsohn 2009; World Bank 2010; UNDP-UNEP 2011). Increased frequency and severity of natural hazards related to climate change can have impact on poverty reduction and development through a number of channels—direct physical impacts, such as damage caused by extreme weather events, indirect impacts, such as increased morbidity after a hazard and fiscal impacts, as hazards create pressure on budgets, often resulting in the reallocation of resources (Prowse and Scott 2008).

Climate change as other shocks would erode whatever attempts farmers have made to accumulate resources and savings (Smit and Wandel 2006). The vulnerability of these smallholder and subsistence farmers is greatly influenced by changes in climate (Rowhani et al. 2011). Households, who lack effective safeguards against risk, are likely to develop a risk aversion behaviour that will further fix them into poverty and vulnerability traps. Poor people tend to be risk-averse to the extent that they are unwilling to invest to create more assets because that involves taking risks that makes them remain poor and vulnerable (Mosley and Verschoor 2005). Thus, understanding the drivers and trajectories of poverty and vulnerability in the face of climate change is critical in the political and development arena (Prowse and Scott 2008; Shewmake 2008).

The aim of this paper is (1) to analyse the micro-level drivers of poverty and vulnerability among smallholder farmers in a changing climate and (2) to improve the availability of micro-level empirical information on local perceptions on and adaptations to climate change, and other socio-economic drivers of poverty and vulnerability for site-specific and generic policy implications in similar

settings. Apart from its contribution to poverty and vulnerability literature in the face of climate change in terms of findings, the paper highlights methodological rigour by using its econometric estimations which is missing in most quantitative studies on poverty and climate change economics (e.g. Gbetibouo 2009; Monirul 2014). In most of poverty studies, variable endogeneity is problematic due to simultaneity leading to biased estimators in econometric models (Wooldridge 2002; Greene 2003). In this regard, the paper applied rigourous GMM and 3SLS econometric models relevant to climate change economic studies (Choi and Fisher 2003; Onofri et al. 2013; Ding and Nunes 2014) but less famed.

Conceptual framework

Climate perturbations will increase with climate change and variability through a timescale. These will shift equilibrium of the social system within a given resilience or coping range. Rising adaptive capacity of the people within the social system is required to reduce risk, poverty and vulnerability. Notably, risk is a function of hazard, exposure, vulnerability and adaptive capacity. Poverty is dynamic but highly stochastic to predict where it will lie in the climate risk-time plane (Fig. 1). The better-off (i.e. non-poor or less poor) may be associated with much resilience or low vulnerability, i.e. wider coping range and less exposure to risk at EQ 2 (Equilibrium 2—low-risk wider coping/resilience range). The worse-off, at EQ 1 (Equilibrium 1—high-risk narrow coping/resilience range), can be gauged to be associated with less resilience, i.e. narrow coping range amid higher exposure to risk hence high vulnerability. The adaptive capacity—through adaptation and mitigation—is required to reduce vulnerability by reducing the level of risk and poverty in order to

improve resilience and widen coping range across time. The pattern of climate risk and poverty time plane might change depending on where the adaptation–resilience path starts. Operationalization of the conceptual framework enables systematic analysis for predicting the level of vulnerability to poverty given different risk, adaptation and resilience factors.

Methodology

The study area

The data set on which our analyses are based was gathered through a household questionnaire survey conducted in Morogoro region between December 2009 and January 2010. Morogoro is the third largest region in Tanzania, occupying 8.2 % (72,939 sq. km) of the country's mainland area with a population of 2,218,492 persons (URT 2013). The region is located between latitude 5° 58′ and 10° 0′ south of the equator and longitude 35° 25′ to the east.

The survey covered six villages (see Fig. 2) in three administrative districts, namely Morogoro rural, Mvomero and Kilosa. The villages covered were Kiwege and Fulwe in Morogoro rural, Mlali in Mvomero district and Rudewa, Msowero and Kigunga in Kilosa district.

The study areas are characterized by the sub-humid agro-climate with varying potentials depending on the amount and distribution of rainfall. The areas receive rainfall ranging between 800 and 2,000 mm per year—following a bimodal regime. The long rain season (locally known as *masika*) starts from March to May and a short rain season from October to December (locally known as *vuli*). Smallholder agriculture accounts for 80–90 % of the region's economic activity. Agriculture is mostly rainfed which makes the sector sensitive to climate change and variability.

Sampling and data collection

Since we intended to use a pooled sample in our econometric estimation, we randomly selected 40 households from six villages to make an overall sample of 240 households—which is by far above the minimum sample suggested by Onwuegbuzie and Collins (2007) and Collins et al. (2009) in detecting moderate effect sizes with 0.8 statistical power at the 5 % level of significance for two-tailed hypotheses. As on average each village had population of around 700 households, our sample covered 6 % of the household population in each village. The village registers were the sampling frames from which the samples were randomly drawn.
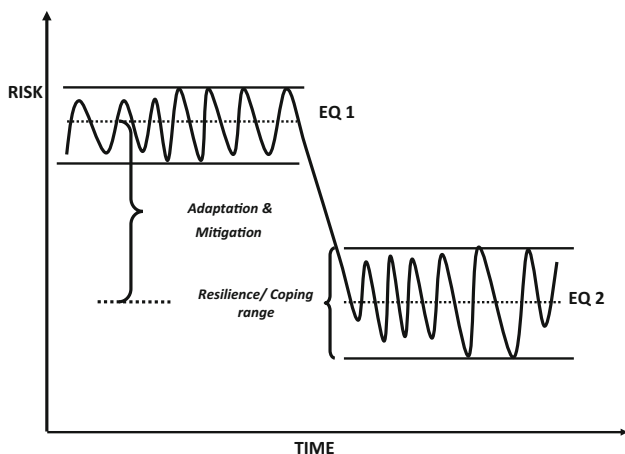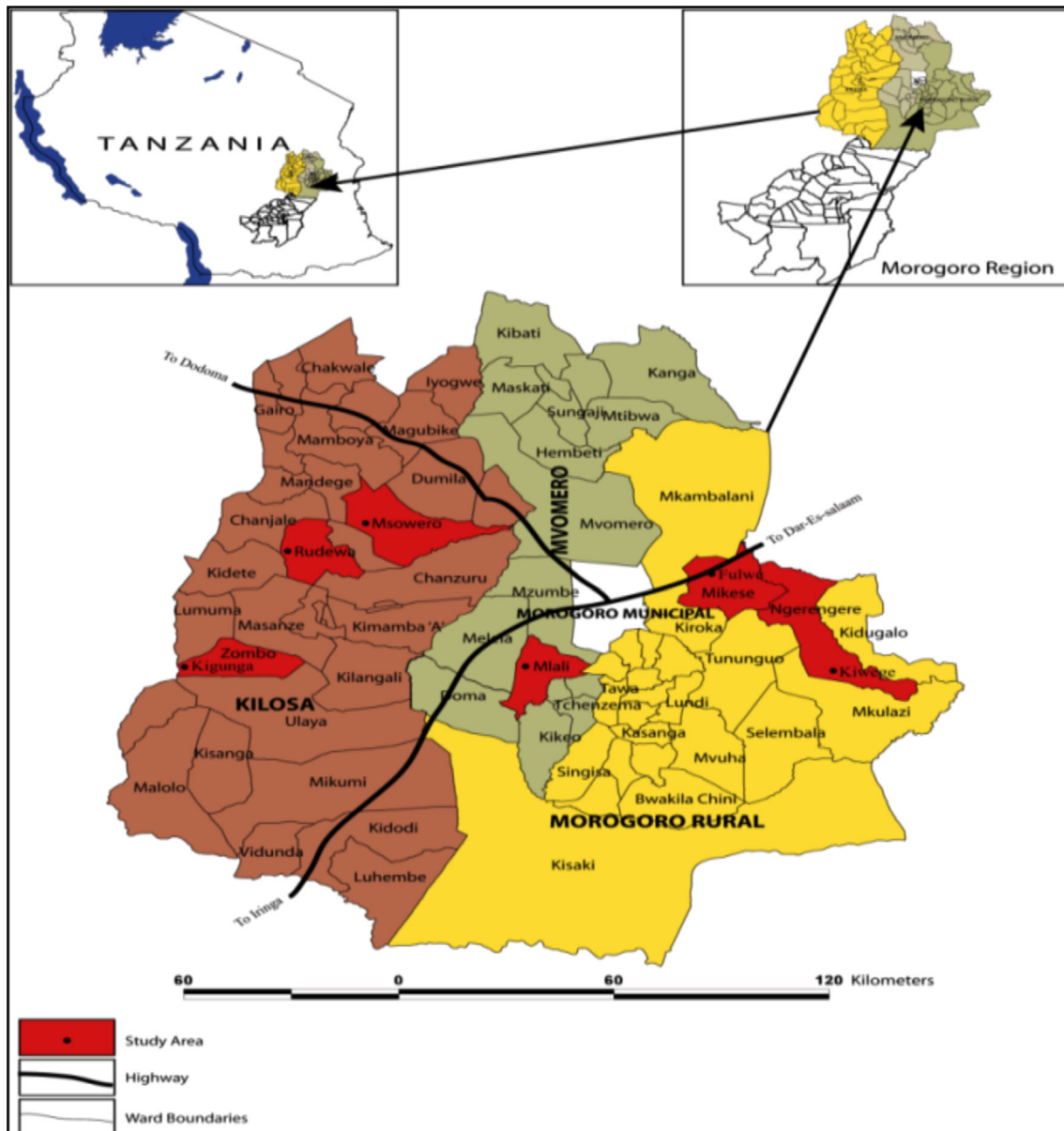

Fig. 1 Climate risk—time plane

Fig. 2 Location of the six study villages

The data were collected using a structured household questionnaire that was administered to sample respondents for 1 month between December 2009 and January 2010. The questionnaire administration involved one researcher and two postgraduate students from Sokoine University of Agriculture based in Morogoro, Tanzania.

Data analysis

Empirical estimation of vulnerability

The econometric methods which use household data to analyse vulnerability involve three approaches: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER) (Hoddinott and Quisumbing 2003; Deressa et al. 2009). VEP was chosen over the rest as due to holding reasons. VEU and VER approaches were far-fetched for this study which neither derived both certainty-equivalent consumption and expected utility nor had panel data to quantify the shock-induced changes. An individual household's vulnerability is the prospect that household becoming poor in the future is currently not poor, or the prospect of it continuing to be poor if currently poor (Christiaensen and Subbarao 2005). Thus, vulnerability is seen as expected poverty, while either consumption or

income is used as a proxy for well-being (Deressa et al. 2009). This method is based on estimating the probability that a given shock or set of shocks such as climate change will move household consumption below a given minimum level (such as below the poverty line) or force the consumption level to stay below the minimum if it is already below this level (Chaudhuri et al. 2002; Chaudhuri 2003).

Under VEP framework, a household is classified vulnerable if it is expected to be poor in the near future. This approach is described and used in other studies (Chaudhuri 2003; Deressa et al. 2009; Rayhan and Grote 2010; Kruy et al. 2010). One of the disadvantages of this method, however, is that the use of estimation made across a single cross section requires the strong assumption that the cross-sectional variability captures temporal variability (Hoddinott and Quisumbing 2003).

According to the VEP, the vulnerability level of a household h at time t is defined as the probability that the household will be in income poverty at time $t + 1$:

$$v_{ht} = \Pr(y_{h,t+1} \leq z) \tag{1}$$

where $y_{i,t+1}$ is the household's per capita income level (welfare indicator) at time $t + 1$ and z is the income poverty line. The stochastic process generating the income of a household h is given by:

$$\ln y_h = X_h \beta + e_h \tag{2}$$

where y_h is per capita income level; X_h represents a mix of observable household socio-demographic and agro-climatic characteristics including household and farm characteristics, agro-climatic conditions and adaptation practices (see Appendix 1 of Supplementary Material); β is a vector of parameters; and e_h is a zero mean disturbance term that captures idiosyncratic factors (shocks) that contribute to different per capita income levels for households that are otherwise observationally equivalent. It is assumed that the variance of e_h is given by:

$$\sigma_{e,h}^2 = X_h \theta \tag{3}$$

We estimate β and θ using a three-step feasible generalized least-squares (FGLS) procedure suggested by Amemiya (1977). In FGLS estimation, the unknown matrix $\sigma_{e,h}^2$ is replaced by a consistent estimator. For details on the orderly steps, see Rayhan and Grote (2010), which are described as follows:

First, the estimation procedure applies the OLS method to Eq. (2) and estimates the residual. Then, the estimated residual is squared to estimate the following equation:

$$\hat{e}_{\text{OLS},h}^2 = X_h \theta + \eta_h \tag{4}$$

For the farming households, $\hat{e}_{\text{OLS},h}^2$ is regressed against a vector of X_h.

Second, the estimate $\hat{\theta}_{\text{OLS}}$ is used to transform the Eq. (4) as follows:

$$\frac{\hat{e}_{\text{OLS},h}^2}{X_h \hat{\theta}_{\text{OLS}}} = \left(\frac{X_h}{X_h \hat{\theta}_{\text{OLS}}} \right) \theta + \frac{\eta_h}{X_h \hat{\theta}_{\text{OLS}}} \tag{5}$$

It is feasible to get a consistent estimate, $X_h \hat{\theta}_{\text{FGLS}}$, of $\sigma_{e,h}^2$, the variance of the shock factor of the household income. The standard deviation can be evaluated as follows:

$$\hat{\sigma}_{e,h} = \sqrt{X_h \hat{\theta}_{\text{FGLS}}} \tag{6}$$

Third, to estimate β, Eq. (2) is transformed as follows:

$$\frac{\ln y_h}{\hat{\sigma}_{e,h}} = \left(\frac{X_h}{\hat{\sigma}_{e,h}} \right) \beta + \frac{e_h}{\hat{\sigma}_{e,h}} \tag{7}$$

An OLS estimation of Eq. (7) gives a consistent and asymptotically efficient estimate $\hat{\beta}_{\text{FGLS}}$ of the parameter β. Therefore, using FGLS estimates of β and θ, the approach finally estimates the expected value and variance of log per capita income (Eq. 8) as follows:

$$\hat{E}[\ln y_h | X_h] = X_h \hat{\beta}_{\text{FGLS}}$$
$$\text{and} \quad Var[\ln y_h | X_h] = \hat{\sigma}_{e,h}^2 = X_h \hat{\theta}_{\text{FGLS}} \tag{8}$$

By assuming income is log-normally distributed, we are then able to use these estimates to form an estimate of the probability that a household with the characteristics, X_h, will be poor, i.e. to estimate the household's vulnerability level. Letting $\varphi(.)$ denote the cumulative density of the standard normal, this estimated probability as presented in Eq. (9) will be given by:

$$\hat{v}_h = \hat{Pr}(\ln y_h < \ln z | X_h) = \left(\frac{\ln z - \{\ln y_h | X_h\}}{\sqrt{Var\{\ln y_h | X_h\}}} \right)$$
$$= \varphi \left(\frac{\ln z - X_h \hat{\beta}}{\sqrt{X_h \hat{\theta}}} \right) \tag{9}$$

The value of $\hat{v}_h$ varies from 0 to 1. The estimate $\hat{v}_h$ thus denotes the vulnerability (VULNER) of the hth household with the characteristics X_h. The vulnerability threshold was assumed to be 0.50. Each household is assigned an estimated degree of vulnerability—the probability that a given household will fall into poverty in future. For income poverty measure, we used the World Bank's dollar poverty line of the US$ 1.25 per capita per day (exchange rate of US$1: TSH 1200).

Furthermore, we classify households broadly into highly vulnerable ($v \geq 0.5$) and less vulnerable ($v < 0.5$) across the current poverty status of poor (I < Z) and non-poor (I ≥ Z) and expected poverty status. The poverty and vulnerability groups were further split into subcategories based on the grouping by Azam and Imai (2009) as indicated in Table 1.

This classification illuminates different poverty and vulnerability trajectories of the households—simply through a descriptive analysis. The analysis was further carried out across the study localities with varying agro-climatic potential. This was aimed at shedding more light on what could be the role of differential climatic advantages and risks on poverty and vulnerability of farming households.

The different groups of the poor in Table 1 are viewed in terms of the vulnerability pathways. Those in the low vulnerability bracket (below the vulnerability threshold of 0.5) comprise the transiently poor and non-poor in cells C and F. Transiently poor in C, they are those currently observed to be poor but they are neither expected nor likely to be poor in the future. Those in F are consistently non-poor now and in the future hence non- or least vulnerable.

The highly vulnerable (at and above the vulnerability threshold of 0.5) consist of those observed to be chronically poor (A) and those transiently poor now still with high probability of being poor in the future (B). The highly vulnerable category comprises the currently non-poor, but they expected to be poor in the future (D) and those currently non-poor but still have some probability of becoming poor in the future (E). Those with relatively high probability of being vulnerable (total vulnerability), exclusive of the non-poor with low vulnerability (F), include those in A, B, D and E. Vulnerability can be further differentiated according to the source of vulnerability, i.e. low level of expected income (A and D) and high income variability (B and E). Some studies that have documented such different groups of poverty vulnerability include Chaudhuri (2003), DelNinno and Marini (2005) and Azam and Imai (2009).

Estimation of drivers of income poverty and vulnerability

(a) Estimation of drivers of income poverty Given that income tends to be endogenously determined with asset-based wealth that was among the predictors of income poverty, we adopted the three-stage least squares (3SLS) which addresses potential endogeneity (Ntim et al. 2013). By using the 3SLS technique, the model explicitly recognizes the endogeneity of changes in income poverty and wealth. The 3SLS estimator involves the 3-stage procedure, the first two being the same as 2SLS, and the seemingly unrelated regression (SUR) estimator is finally applied. The 3SLS technique is very common in income—poverty studies (Taylor et al. 1997; Quang Dao 2009; Ngepah 2011), but less common in income vulnerability due to climate change literature (Tessema et al. 2013; Dodo 2014).

The 3SLS estimator has desirable properties. Nevertheless, if the error term is correlated with one or more explanatory variables, then the 3SLS estimator is biased particularly with small samples. However, the 3SLS estimator is consistent and asymptotically more efficient than single-equation OLS estimators (Jacques and Nigro 1997; Ntim et al. 2013).

The income equation to be estimated and the identifying instruments are as follows in Eqs. (10)–(12):

$$Y = \alpha + bY_1 + cX + \mu \tag{10}$$

$$X = HHAGE\ HHAGESQ\ HHSIZE\ HSIZESQ\ LABFC \\ LABFCSQ\ FAMEX\ FAMEXSQ\ CCANTH\ EXTENS \\ LANDSQ\ TACADAP\ POTLOC\ OFFARM\ LAND\ CREDIT$$

$$Z = identifying\ instruments\ (INCOME\ STRADAP\ HHEDUC) \tag{12}$$

where Y is the dependent variable (i.e. income); Y_1 is a vector of one or more predictor variables that we believe may or may not be endogenous (i.e. WEALTHX); X is a vector of right-hand side variables we believe are exogenous (see descriptions of variables in Appendix 1 of

Table 1 Classification of household poverty and vulnerability trajectories

Vulnerability (1)	Observed poverty status (Based on current income)		Expected income poverty status (4)
	Poor [I < Z] (2)	Non-poor [I ≥ Z] (3)	
Highly vulnerable ν ≥ 0.5	A	D	Poor E(I) < Z
	B	E	Non-poor
Non-vulnerable ν < 0.5	C	F	E(I) ≥ Z
Poor = A + B + C			*High vulnerability = A + B + D + E*
Chronically poor = A			*Low level of income = A + D*
Frequently poor = B			*High variability of income = B + E*
Transient poor = B + C			*Non-vulnerable = C + F*
Vulnerable to chronic poverty = D			*Total vulnerability = A + B + C + D + E*

Source: Adapted from DelNinno and Marini (2005) and Azam and Imai (2009)

Supplementary Material); α is the intercept; b and c are vectors of slope coefficients attached to the variables in Y_1 and X, respectively; Z is a vector of exogenous variables (i.e. INCOME, STRADAP and HHEDUC) that are excluded from Eq. (10), and therefore used as identifying instruments for the endogenous variable (WEALTHX) (see descriptions in Appendix 1 of Supplementary Material) in Y_1; and μ is the error term. Though climate change scientists consider these variables or its proxies relevant in understanding climate change effects to marginalized (Thomson et al. 2014; Robertson et al. 2014), only a few existing climate change-income vulnerability empirical studies used same or proxy of these variables (Tessema et al. 2013). In this model, tactical adaptation strategies bundle (TACADAP) representing the intensity of adopted adaptation strategies from the potential adaptation options relevant in the area. Tactical adaptation strategies are done in a year or prevailing season within a shorter planning and decisional timescale to cope with the changing seasonal agro-climatic condition (see Hassan and Nhemachena 2008; Nhemachena et al. 2014). The tactical adaptation bundle category includes reduction in cropland size to be planted, changing planting date and adjustment in timing of farm operations, e.g. early land preparation and sowing before the first rains. Strategic adaptations that include irrigation, fertilizer use and agroforestry are adaptation options planned over a long term beyond a season or a year to manage production-related climate risks (see Anwar et al. 2013). The very nature of such strategic adaptations suggests a potential correlation with income and wealth hence were used as identifying instrument in the 3SLS model.

(b) Estimation of drivers of vulnerability Overall vulnerability An omnipresent problem in cross-sectional studies on poverty and vulnerability due to climate change is heteroskedasticity (Dixon et al. 1994; Deschênes and Greenstone 2011; Opiyo et al. 2014). Income and related models tend to have simultaneity relationship with or more of their regressors such as wealth leading to an endogeneity problem. The usual approach when facing heteroskedasticity of unknown form is to use the generalized method of moments (GMM) introduced by Hansen (1982). GMM makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroskedasticity of unknown form. The GMM estimator has been derived from a family of standard instrumental variables (IV) estimators (Baum et al. 2003). A handful of climate change-related vulnerability studies (Soto Arriagada 2005; Carmen Martinez-ballesta et al. 2009; Aroca and Ruiz-Lozano 2009; Muris 2011) have employed GMM. We begin with the standard IV estimator and then relate it to the GMM framework as follows: The equation to be estimated is, in matrix notation as presented in Eqs. (13, 14):

$$y = X\beta + u \quad E(uu') = \Omega \tag{13}$$

with typical row

$$y_i = X_i\beta + u_i \tag{14}$$

The matrix of regressors X is $n \times K$, where n the number of observations. The error term u is distributed with mean zero and the covariance matrix Ω is $n \times n$. Two special cases for Ω that we will consider are presented in Eqs. (15) and (16):

Homoskedasticity: $\quad \Omega = \sigma^2 I \tag{15}$

Heteroskedasticity: $\quad \Omega = \begin{bmatrix} \sigma^2 I & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma^2 n \end{bmatrix} \tag{16}$

Some of the regressors are endogenous, so that $(X_i u_i) \neq 0$. We partition the set of regressors into $[X_1 X_2]$, with the K_1 regressors X_1 assumed under the null hypothesis to be endogenous, and the $(K-K_1)$ remaining regressors X_2 assumed exogenous. The set of instrumental variables is Z and is $n \times L$; this is the full set of variables that are assumed to be exogenous; i.e. $E(Z_i u_i) = 0$. We partition the instruments into $[Z_1 Z_2]$, where the L_1 instruments Z_1 are excluded instruments, and the remaining $(L-L_1)$ instruments $Z_2 \equiv X_2$ are included instruments/exogenous regressors as presented in Eqs. (17, 18):

Regressors $X = [X_1 X_2] = [X_1 Z_2]$
$\quad\quad\quad\quad = [Endogenous\, Exogenous] \tag{17}$

Instruments $Z = [Z_1 Z_2] = [Excluded\, Included] \tag{18}$

The matrix order condition for identification of the equation is $L \geq K$; there must be at least as many excluded instruments as there are endogenous regressors. If $L = K$, the equation is said to be "exactly identified"; if $L > K$, the equation is "overidentified". The projection matrix $Z(Z'Z)^{-1}Z'$ is denoted by P_Z. The instrumental variables estimator of β is as follows in Eq. 20:

$$\hat{\beta}_{IV} = \left\{ X'Z(Z'Z)^{-1}Z'X \right\}^{-1} X'Z(Z'Z)^{-1}Z'y$$
$$= (X'P_Z X)^{-1} X'P_Z y \tag{19}$$

Now, since the standard IV estimator is a special case of a generalized method of moments (GMM) estimator, GMM follows the assumption that the instruments Z are exogenous can be expressed as $E(Z_i u_i) = 0$. The L instruments give us a set of L moments (Eq. 20):

$$g_i(\hat{\beta}) = Z_i'\hat{u}_i = Z_i'(y_i - X_i\hat{\beta}) \tag{20}$$

where g_i is $L \times 1$. The exogeneity of the instruments means that there are L moment conditions, or orthogonality conditions, that will be satisfied at the true value of β such that

$E\{g_i(\beta)\} = 0$. Each of the L moment equations corresponds to a sample moment, and we write these L sample moments as $\bar{g}(\hat{\beta}) = \frac{1}{n}\sum_{i=1}^{n} g_i(\hat{\beta}) = \frac{1}{n}\sum_{i=1}^{n} Z_i'(y_i - X_i\hat{\beta}) = \frac{1}{n}Z'\hat{u}$. The intuition behind GMM is to choose an estimator for β that solves $\bar{g}(\hat{\beta}) = 0$. If the equation to be estimated is exactly identified, so that $L = K$, then we have as many equations—the L moment conditions as we do have for unknowns in the K coefficients for estimating $\hat{\beta}$. In this case, it is possible to find a $\hat{\beta}$ that solves $\bar{g}(\hat{\beta}) = 0$, and this GMM estimators in fact the IV estimator. If the equation is over-identified, however, so that $L > K$, then we have more equations than we do unknowns, and in general it will not be possible to find a $\hat{\beta}$ that will set all L sample moment conditions to exactly zero. In this case, we take an $L \times L$ weighting matrix W and use it to construct a quadratic form in the moment conditions. This gives us the GMM objective function (Eq. 21):

$$J(\hat{\beta}) = n\bar{g}(\hat{\beta})' W \bar{g}(\hat{\beta}) \tag{21}$$

A GMM estimator for β is the $\hat{\beta}$ that minimizes $J(\hat{\beta})$. Deriving and solving the K first-order conditions,

$$\frac{\partial J(\hat{\beta})}{\partial \hat{\beta}} = 0$$

generates the GMM estimator (Eq. 22):

$$\hat{\beta}_{GMM} = (X'ZWZ'X)^{-1} X'ZWZ'y \tag{22}$$

Note that the results of the minimization, and hence the GMM estimator, will be the same for weighting matrices that differ by a constant of proportionality. In this study, y and X are defined in Eq. (23), Xs in Eqs. (24) and (25), and Z in Eq. (26) below. The variables are further described in Appendix 1 of Supplementary Material. In short,

$$y = vulnerability \tag{23}$$

$$X_1 = wealth \tag{24}$$

$$\begin{aligned} X_2 = \; & SEXHEAD \; HHAGE \; HHAGESQ \; HHSIZE \; HSIZESQ \\ & LABFC \; LABFCSQ \; FAMEX \; FAMEXSQ \; CCANTH \\ & EXTENS \; HHEDUC \; LANDSQ \; TACADAP \; POTLOC \; CREDIT \end{aligned} \tag{25}$$

$$Z_2 = INCOME \; OFFARM \; LAND \tag{26}$$

Therefore, the equation to be estimated in (Eq. 13) above has $\hat{\beta} = \hat{\beta}_{GMM}$.

Differential household vulnerability The sample households were not in the same boat regarding the factors underlying their vulnerability level. GMM estimation framework was applied on the overall vulnerability score and different sects of the sample according to the vulnerability level—with cut-offs at the first quartile, second quartile (median) and third quartile. The choice of GMM estimation over quantile regression was based on the desirable properties of the GMM framework which is more efficient and consistent, as the latter is similar to standard linear regression, except that the conditional expectation $E(Y/X)$ is replaced by a conditional quantile which is equally prone to endogeneity as explained above. In order, to allow the model to reflect drivers of poverty and vulnerability in the face of climate change, the estimated models fitted climate-related variables including tactical adaptations (TACADAP), strategic adaptations (STRADAP) and farmers' perception on whether they believe that human activities caused climatic changes (CCANTH).

Results and discussion

Poverty and vulnerability: a descriptive illumination

The average household income per capita was much lower in the agro-climatically low potential areas compared to relatively potential areas (Table 2). A typical household (at the medial position) in the high potential area had an income per capita which was twice as much (US\$ 0.27 vs. US\$ 0.12 and 0.14) of a typical household in agro-climatically less-favoured areas. Within both the poorest group (first quartile) and rich group (third quartile), the income of households in high potential area was much higher compared to those in the low and medium potential areas.

Based on the medial per capita income of US\$ 0.17 which represents a typical household, the abject poverty is deep among households in the study area. In this respect, measures to address income poverty should be on top of the development agenda. Impliedly, delivery of MDG on halving the abject poverty by 2015 can hardly be achieved.

Generally, a typical household had 45 % probability of being vulnerable in future. Households in low potential areas were more vulnerable than those residing in potential areas. The probability of households residing in the low potential areas falling under the most vulnerable category (third quartile) was more than twice as much higher than that of those in the similar category found in high potential areas (0.95 vs. 0.44). The pattern of descriptive statistics suggests an overlap between current poverty and future vulnerability.

Given the level of poverty and vulnerability in the area, any other shocks such as climate change will adversely impact the farming households. The future climate change is expected to amplify poverty and vulnerability of those already poor and vulnerable today (see Gbetibouo and Ringler 2009).

Table 2 Descriptives of household income poverty and vulnerability

Items	High potential (n = 80)	Moderate potential (n = 80)	Low potential (n = 80)	Overall (n = 240)
Daily household income per capita (USD)				
Mean	1.32	1.45	0.34	1.04
SD	4.05	10.18	0.76	6.34
Median	0.27	0.14	0.12	0.17
Inter-quartile range	0.80	0.39	0.23	0.45
First quartile	0.11	0.04	0.07	0.07
Third quartile	0.92	0.43	0.29	0.51
Household vulnerability scores (probabilities)				
Mean	0.49	0.49	0.52	0.50
SD	0.36	0.34	0.35	0.35
Median	0.44	0.45	0.47	0.45
Inter-quartile range	0.73	0.61	0.74	0.67
First quartile	0.15	0.17	0.21	0.18
Third quartile	0.44	0.78	0.95	0.86

Source: Own survey (2010)

Results in Table 3 indicate that there were more non-vulnerable non-poor households (50 %: 4 out of 8) in the agro-climatically high-potential villages than in the rest of localities. Those in the non-vulnerable band comprised majority (67 %) from the high potential area. These are regarded as more secure and risk-proofed now and in the future. Agro-climatic advantages enhance income generation from the weather-dependent agricultural production and set grounds for a resilient future.

Transient non-vulnerable poor households that were observed to be poor but were neither expected to be poor nor likely to be poor in the future were the majority in the agro-climatically favoured area (65 %: 26 out of 40). These are the ones whose poverty is transient as documented in poverty literature (see Dramani 2012). Although their incomes fall below the poverty line, they are not expected to be poor in the future. Higher incidence of transient poverty in agro-climatically advantaged localities suggests a promising path the households are treading out of current poverty and vulnerability. Such anticipated prospect seems to be limited among the farming households in agro-climatically less advantaged. In the study area, the future climate is predicted to impact negatively on agricultural production mainly through low erratic rainfall and seasonal shifts. The livelihoods of most of farmers in the agro-climatically less-favoured area that seem to be poorer and vulnerable are expected to be disrupted with future shocks such as climate change.

Irrespective of agro-climatic differences, majority of the households they still fall in the category of a broad vulnerable group—with high volatility of income being the main source of vulnerability accounting for 47 % of the sample households (112 out of 240).

Apparently, about 80 % (192 out of 240) sample households were vulnerable in different ways (Table 3). However, households strode different paths of poverty and vulnerability trajectories. In this regard, it is policy-relevant to address current poverty and future vulnerability in the area. However, this requires a rigorous analysis of micro-level determinants of poverty and vulnerability.

Micro-level drivers of poverty and vulnerability

Generally, two models were estimated—the 3SLS that estimated predictors of income poverty and GMM that were run for the overall vulnerability and within three quartiles (Table 4). The decision to 3SLS model instead OLS was to address the problem of endogeneity stemming from simultaneity between wealth and income. Tests of endogeneity, strength and relevance of instruments indicate that the 3SLS model was relevant. For GMM, relevance and weakness of instruments were also tested against the inconsistency of OLS—and the tests confirm that it was appropriate. The R-square values and significance levels of the models indicate that the fitted predictors explained the variation in the dependent variables and fitted the data well.

Age of the household head had a significant ($P < 0.05$) inverse relationship with vulnerability—for the overall sample and among the households in the highly vulnerability sect of 75th percentile of the vulnerability scores. Ageing is widely perceived to be associated with higher vulnerability and insecurity (see Abunuwasi and Mwami 2001; Barrientos 2007; Mwanyangala et al. 2010). However, in some cases, ageing may be associated with accumulation of assets, experiences and skills and social capital that would forge livelihood resilience—hence reducing vulnerability. Furthermore, the age of the household head appeared to have a significant ($P < 0.05$) inverse relationship with vulnerability—among both the households in the overall sample and high vulnerability sect in the third vulnerability quartile. This would have been so due to the fact that on average the household heads were relatively in the economically active mid-age of 45 years. In Tanzania, the old age starts from the age of 60 years and above according to the national policy on the ageing (URT 2003). However, with exponential increase in age which apart from testing for linearity captures the effect of ageing on vulnerability—it turned out that vulnerability increased significantly with ageing. Old age tends to correlate with vulnerability and social insecurity (Abunuwasi and Mwami 2001; Barrientos 2007). Because of a range of psychological, physiological and socio-economic dispositions, older people are more vulnerable to the impacts of climate change and weather extremes (Harvison et al. 2011).

Table 3 Incidence of vulnerability (counts) across localities

Type	Category	High potential	Moderate potential	Low potential	Overall
F	Non-vulnerable non-poor	4	2	2	8
C	Transient poor	26	8	6	40
F + C	Total non-vulnerable	30	10	8	48
E	High variability of income	9	4	1	14
B	Frequently poor	28	34	36	98
B + E	Total highly variable income (vulnerable)	37	38	37	112
D	Vulnerable to chronic poverty	13	32	35	80
A	Chronically poor	0	0	0	0
A + D	Total low income (vulnerable)	13	32	35	80
Total vulnerability		50	70	72	192

Source: Own Survey (2010)

Therefore, reducing vulnerability among the elderly people should be an important agenda in the poverty and vulnerability reduction programming in the face of climate change.

The household size had significant inverse relationships with income, and vulnerability of those within the lower sect of vulnerability band (first vulnerability quartile). This means, large-sized households tended to be poorer than their counterpart small-sized households—the finding dominating the landscape of poverty literature on developing countries (e.g. IFAD 2001; Anyanwu 2013a). In contrast, the relatively large-sized households tended to be less vulnerable particularly those that fall in the lower vulnerability band. Arguably, the current poverty does not always explain the future poverty and vulnerability—as Shewmake (2008) argues that the transiently poor of today would have means of escaping poverty in future. However, the relationships between household size and poverty and vulnerability are nonlinear in nature as revealed through the effect of squared household size on income, and vulnerability particularly among households in the lower vulnerability sect (first quartile).

Based on such findings, we argue that the implications of household demographic structure on livelihood processes and outcomes are complex and arguable—as it is for the linkages between population and development at a national scale (see Merrick 2002). However, the methodological treatment of household size may lead to different results in poverty analysis. Meenakshi and Ray (2000) and Mok et al. (2011) advocate the need to adjust the household size to size economies and composition in terms of adult equivalence scale for deflating income. In our approach, we used unadjusted household size as we did not collect disaggregated age data of individual household members—there are several studies that treated household size the same way in poverty and development, and climate change adaptation literature (see Kamuzora and Mkanta 2000; Bogale et al. 2005; Tessema et al. 2013; Tufa et al. 2014).

Farming experiences in terms of years spent in farming mattered significantly ($P < 0.01$) in reducing vulnerabilities of the entire sample and across the three modelled sects of sample households—first quartile, median and the third quartile. The farming experience is widely identified as one of the factors enhancing farming efficiency—hence improving farm returns on investment and ultimately income. As a result, years in farming as a proxy measure of farming experience is widely fitted in the farm technical efficiency estimation models (see Obasi et al. 2013; Mlote et al. 2013; Anyanwu 2013b). However, the relationship was nonlinear as an exponential increase in years in farming increased the vulnerability—meaning that increased farming experience does not constantly reduce vulnerability.

Farmers who perceived that climate change is human-induced tended to have significantly ($P < 0.05$) higher income. By perceiving that climate change with its associated risks is due to human actions, such farmers are likely to device adaptation strategies that end up enhancing their incomes and resilience. According to Swim et al. (2011), adapting to, and coping with, climate change is dynamic; it involves many intra-psychic processes that influence reactions to (and preparations for) adverse impacts of climate change, including chronic environmental conditions and extreme events. Arbuckle et al. (2013) found that farmers who were concerned about the impacts of climate change on agriculture and attributed it to human activities had more positive attitudes toward both adaptive and mitigative management strategies.

The household income increased significantly ($P < 0.01$) with size of farm managed by the household. Access to land is critical for agricultural production which is the major source of income and food. Due to limited use of fertilizer and other productivity-enhancing technologies, increasing the farm size remains to be the major means of realizing increased farm output. The farm size was instrumented in the case of vulnerability models hence not fitted as a predictor variable. However, the squared farm size reduced vulnerability significantly ($P < 0.05$) on the

Table 4 Three-stage least squares (3SLS) and GMM estimates of income poverty and vulnerability

Variables	Description		3SLS reg on Income	GMM regression on vulnerability (VULNER)			
	Mean	SD		All	First quartile	Median	Third quartile
Income equation							
Wealth (WEALTHX)	0.31	0.46	0.0581	(Instrumented) 0.014	0.029	−0.004	0.01
Sex of the household head (SEXHEAD)	NA			−0.023	−0.236	0.045	0.075
Age of household head (HHAGE)	45.37	15.7	−0.0092	−0.043**	−0.008	−0.01	−0.052**
Age of household head squared (HHAGESQ)	2304.11	1584.74	−0.0001	0.000***	0	0	0.001**
Household size (HHSIZE)	4.35	2.4	−0.4094***	0.033	−0.250*	−0.072	0.052
Household size squared (HHSIZESQ)	24.64	28.66	0.0187**	−0.003	0.023*	0.007	−0.005
Labour force (LABFC)	2.51	1.23	−0.0748	0.073	0.32	0.069	0.058
Labour force squared (LABFCSQ)	7.83	8.58	0.0114	−0.017	−0.071	−0.012	−0.013
Farming experience (FAMEX)	20.8	15.11	−0.0026	−0.098***	−0.881***	−0.315***	−0.123***
Farm experience squared (FAMEXSQ)	659.94	833.71	0.0001	0.001***	0.010***	0.003***	0.001***
Perceive climate change to be anthropogenic (CCANTH)	0.48	0.5	0.3455**	0.017	0.005	0.143	0.047
Access to extension (EXTENS)	0.84	0.37	−0.0532	0.135	0.172	0.096	0.175
Land size (acres) (LAND)	4.42	3.57	0.1473**	Instrument	NA		
Land size squared (acres) (LANDSQ)	32.23	74.36	−0.0035	−0.002**	−0.007***	−0.003**	−0.002**
Tactical adaptations (e.g. early planting, adjust farm size to be planted) (TACADAP)	0.77	0.3	−0.0377	−0.025	−0.19	0.194	−0.044
High potential locality ((POTLOC)	0.33	0.47	0.7858**	−0.071	−0.505	−0.045	−0.06
Access to credit (CREDIT)	0.93	0.26	−0.5403	0.201	0.005	0.066	0.255
Whether self-employed in non-agriculture (OFFARM)	0.31	0.46	0.7109	Instrument	NA		
Long-term wealth index squared (WEALTHXSQ)	0.93	0.26	0.0187	NA			
Constant			−0.0026	0.963*	16.142***	4.014***	1.413*
Wealth equation							
Income logged (INCOME)	−1.57	1.48	1.7425**	Instrument	NA		
Strategic adaptations (e.g. irrigation, fertilizer and agroforestry) (STRADAP)	0.24	0.27	0.7858	NA			
Education household head (HHEDUC)	0.74	0.44	−0.0026**	0.056	0.057	0.015	0.056
R^2			46 %	76 %	63 %	68 %	69 %
N			238	229	57	114	169

NA not applicable for respective variable

*, ** and *** significant at $P < 0.1$, $P < 0.05$ and $P < 0.01$, respectively. *F*-statistic on the excluded instruments in the first stage is greater than 10, one should not worry about instruments strength

overall sample and across quantiles. Given small-sized farm plots (average of 1–2 ha) that lack economies of scales, an increase in farm size which is still within the limits of other household resources particularly family labour would increase farm output and livelihood resilience. However, in the sub-humid dryland farming condition, farm expansion amid climate change might reduce productivity of land due to limited soil moisture for crop production hence lowering farm income. In this case, intensification with smaller manageable plots will be ideal with efforts aimed at capturing and optimizing the use of moisture such as supplementary irrigation and in situ rainwater harvesting.

Households in localities with higher agro-climatic potential tended to have significantly ($P < 0.01$) higher income than those in the remaining localities. Higher agricultural productivity in high potential areas contributes to increased farm income, hence reduced level of income poverty. The farming system in agro-ecologically less potential faces more climate-related production risks that limits farm productivity hence contributing to poverty (Hatibu et al. 2006).

The income significantly ($P < 0.05$) increased the level of asset-based wealth. Three-stage least-squares estimation helped to resolve the problem of simultaneity between income and wealth that would have impaired estimates in case of OLS. The income enhances the purchasing power hence enabling accumulation of assets and affording improved amenities that were used to construct the wealth variable. Gbetibouo (2009) and Shiferaw (1998) reported that wealth reflecting past cumulative income achievements of households enhances the ability of bearing risks hence forging resilience to climate change. At the same time, Aikaeli (2010) and Harvey et al. (2014) found that household income and physical assets possession explain wealth. It is this simultaneity nature of income and wealth in the study area that compelled the application of 3SLS estimation.

The formal education of the household head had a significant ($P < 0.005$) negative relationship with income. The level of formal education attained was primary education. It seems the primary level education was not adequate to contribute to increased income. Even a farmer who did not attend primary school still had a chance of being better-off in terms of income. Anyanwu (2013a) found that it was post-secondary education that reduced the probability of being poor in Nigeria.

Conclusions

The income poverty was prevalent in the study area. The income poverty was relatively higher in agro-climatically less-favoured than in potential areas. Over three quarters of the sample households were vulnerable in different fronts. The pattern of future vulnerability tended to overlap with poverty distribution across localities. A large proportion of households in the high potential area were identified in the non-poor non-vulnerable band compared to low potential area for the same poverty vulnerability band. Majority of the households found to be poor in the agro-climatically potential area was in transient poverty as they were neither expected to be poor nor likely to be poor in the future. Thus, any other shocks such as climate change will adversely impact the agro-climatically less-favoured areas where the poor and vulnerable are the majority.

Ageing of the household head beyond an economically active age tended to increase vulnerability. Therefore, reducing vulnerability among the elderly people should be an important agenda in the poverty and vulnerability reduction programming. A decade ago, some African countries including Swaziland, Lethoto and Botswana have introduced the non-contributory pension schemes to address the old-age-related poverty and vulnerability. The same has been argued for in Tanzania by old-age lobbyists and activists such as HelpAge International. The Government of Tanzania already provides free health care for elderly people, but a comprehensive social security scheme that covers a range of vulnerability spheres around old age is necessary.

Large-sized households tended to be income-poor, but lacking linearity consistence. However, households in the low vulnerability sect tended to be less vulnerable with increasing household size. Our results on the influence of household size on poverty and vulnerability are rather inconclusive. Indeed, the household size as a demographic cycle variable interacts with other life cycles and livelihood initiatives in a complex way. The outcome of such interactions is verily not straight to ascertain.

Farming experience reduced the probability of future vulnerability. However, the relationship with vulnerabilities was reversed when the farming experience was increased exponentially—indicating nonlinearity. Years in farming can enhance practical experience and skills from life-course learning and extension services that may translate into increased labour productivity and ultimately increased livelihood resilience. However, many years in farming may be associated with over use of farm plots that would reduce productivity and farm income. This is not an exception in African smallholder farming which is increasingly characterized by limited use of fertilizer coupled with limited fallow periods to replenish the mined soil nutrients.

Farmers' perception that climate change is associated with human activities would entice them to adopt mitigation and adaptation measures in the production systems that also increase their incomes. In this regard, policy-makers

have a change of exploiting this perception to promote adaptation and mitigation strategies in a win–win scenario that addresses climate change and income poverty at the same time. Increasing farm size tended to enhance the income level. However, increasing the farm size exponentially reduced the level of vulnerability. However, we argue that expanding the area under farming should be within the resource limits of the household, family labour in particular.

The household income enhanced the level of wealth. Durable assets and housing amenities were the core constructs of wealth index. In this respect, high income will inevitably contribute to accumulation of assets and affording living standard-enhancing utilities. Therefore, enhancing rural incomes will result into assets formation and improvement of living standards, which in long-term build livelihood resilience. Recent integrated climate change assessment already suggests that climate change will aggravate the poverty rates by affecting income from the crop sub-sector.

Therefore, empirical understanding about what drives the poverty and vulnerability trajectories of smallholder farmers is imperative to informed policy planning for addressing the adverse future climate impacts.

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